

Article

An Intelligent Method for Bearing Pad Flatness Inspection Based on UAV-Enabled 3D Reconstruction

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Abstract

The flatness of bearing pads directly affects structural load transfer safety. However, conventional total station-based inspection methods suffer from limited spatial sampling, low inspection efficiency, and high safety risks associated with working at height. To address these limitations, this paper proposes UAV-FIBP (Unmanned Aerial Vehicle-based Flatness Inspection for Bridge Pads), an automated and intelligent method for pad flatness assessment utilizing UAV-based 3D reconstruction. By designing a close-range, multi-orbit circumnavigational UAV flight path and acquiring high-overlap imagery (85% forward and 80% side overlap), a millimeter-accurate 3D model is generated via photogrammetry, achieving a high-density point cloud of ≥ 200 points/cm² on the pad surface. Following point cloud denoising and region-of-interest segmentation using the Random Sample Consensus (RANSAC) algorithm, Principal Component Analysis (PCA) is employed to fit a reference plane. A dual-parameter evaluation framework is subsequently introduced: the root mean square (RMS) deviation quantifies local surface roughness, while the maximum elevation difference is derived from the angle between the normal vectors of the fitted plane and the horizontal plane, thereby enabling a comprehensive assessment of global inclination. Validation experiments conducted on laboratory-scale setups and real construction sites (involving four bridge pads) demonstrate that the proposed method achieves deviations ≤ 2 mm compared to total station measurements, satisfying the requirements stipulated in the Standards for Quality Inspection and Verification of Highways (JTG F80/1-2017). Results indicate that UAV-FIBP enables non-contact, full-coverage, and automated flatness inspection, significantly improving inspection efficiency and construction safety. This work establishes a scalable technical pathway for intelligent bridge construction.



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Keywords: bearing pads; flatness inspection; unmanned aerial vehicle; flight path planning; 3D reconstruction

1. Introduction

Bridge bearing pads [1] serve as critical load-transferring components connecting the cap beam and the box girder bearings [2,3]. The flatness of the bearing pad top surface directly influences the contact condition between bearings and the uniformity of load distribution [4]. Uneven bearing pads can cause localized stress concentration, accelerate bearing degradation, and even trigger structural failure, posing a serious threat to the

operational safety of bridge structures. Therefore, high-precision, full-coverage quality inspection of bearing pad flatness during construction is a crucial step in ensuring the long-term durability and safety of bridge structures.

Currently, flatness inspection of bearing pads primarily relies on total station-based pointwise elevation measurements [5,6]. This approach typically samples only corner points or a limited number of measurement locations, resulting in low spatial sampling density [7]. Consequently, it fails to capture local surface irregularities and subtle undulations, introducing significant random errors and the risk of missing defects. In particular, under conditions involving tall piers or complex terrain, manual prism placement requires workers to ascend to height, leading not only to low operational efficiency but also to safety hazards associated with elevated work and limitations in site accessibility [4]. These shortcomings render conventional methods inadequate for meeting the demands of modern intelligent construction, which requires efficient, safe, and comprehensive quality control.

In recent years, unmanned aerial vehicle (UAV) photogrammetry has gained widespread application in macro-level bridge damage detection—such as crack identification and deformation monitoring—owing to its operational flexibility, non-contact operation, and high spatial coverage [8]. However, existing studies have largely focused on large-scale structural surface damages [8,9]. For small yet critical components like bearing pads, which are typically around $0.5\text{ m} \times 0.5\text{ m}$ in size and require high geometric accuracy ($\leq 2\text{ mm}$), effective methods suitable for micro-scale surface precision inspection are still lacking. More importantly, traditional evaluations often rely solely on elevation differences between corner points, lacking a comprehensive quantitative framework that accounts for both local surface roughness (i.e., floor flatness) and global inclination (i.e., floor levelness) [10], thereby failing to fully characterize the actual flatness condition of the bearing pad [4,7].

To address these technical gaps, this paper proposes an automated intelligent method for bridge pad flatness inspection based on UAV-enabled 3D reconstruction, termed Unmanned Aerial Vehicle-based Flatness Inspection for Bridge Pads (UAV-FIBP). By designing a circumnavigational flight path [11] to achieve high-overlap image acquisition, a millimeter-level accurate 3D model is reconstructed. Robust plane fitting is then performed by integrating the Random Sample Consensus (RANSAC) algorithm [12,13] with Principal Component Analysis (PCA) [14]. Furthermore, a novel dual-parameter evaluation framework is introduced: the root mean square (RMS) deviation quantifies local surface roughness, while the maximum elevation difference—derived from the angular deviation of the fitted plane from the horizontal—assesses global inclination. The proposed method enables end-to-end automation from data acquisition and 3D reconstruction to intelligent assessment, overcoming the sampling limitations and safety risks of conventional approaches. It provides an efficient, safe, and scalable technical solution for quality control in bridge construction.

2. Method

This paper proposes a UAV-based framework for flatness inspection of bridge bearing pads, termed UAV-FIBP, aiming to overcome the limitations of conventional point-wise measurement methods in terms of efficiency, safety, and spatial coverage. The framework enables efficient, safe, and comprehensive automated assessment of bridge bearing pad flatness [5]. The overall workflow of UAV-FIBP is illustrated in Figure 1. At its core is an integrated “reconstruction–processing–evaluation” pipeline that transforms multi-view images into quantified flatness metrics through three sequentially connected stages.

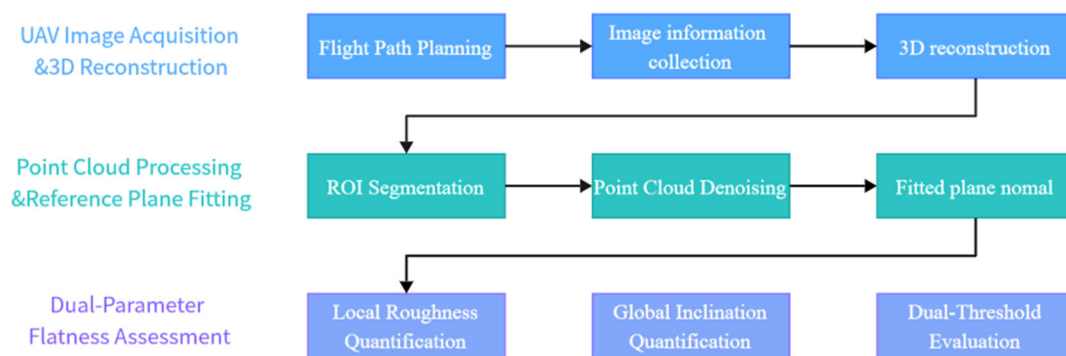


Figure 1. Workflow of the UAV-FIBP method. The pipeline consists of three main stages: (1) UAV-based multi-view image acquisition and 3D reconstruction (Light Blue), (2) point cloud denoising and plane fitting using RANSAC and PCA (Teal), and (3) dual-parameter flatness assessment using RMS deviation and maximum elevation difference (Light Purple).

2.1. UAV-Based Multi-View Image Acquisition and 3D Reconstruction

This stage aims to generate a high-precision 3D point cloud model [15–17] of the bridge bearing pad. The UAV performs close-range, multi-orbit circumnavigational flights around a single bridge pier to capture oblique images with high overlap [18,19]. Using photogrammetric software [20], an accurate 3D model containing detailed surface geometry of the bearing pad is reconstructed via Structure-from-Motion (SfM) [21,22] and Multi-view Stereo (MVS) [23] techniques [24].

2.1.1. UAV Circumnavigation Flight Path Planning

To ensure adequate and highly overlapping image coverage [25] of the bearing pad surface, a circumnavigational flight strategy is employed [26,27]. The UAV flies along horizontal circular orbits at varying radii and heights (e.g., 2 m and 2 m, 3 m and 3 m, and 4 m and 4 m) centered on the bearing pad (Figure 2), thereby enabling comprehensive imaging of the pad from multiple heights and viewing angles. This strategy effectively mitigates occlusion issues associated with single-viewpoint imaging and enhances image quality, particularly in edge regions.

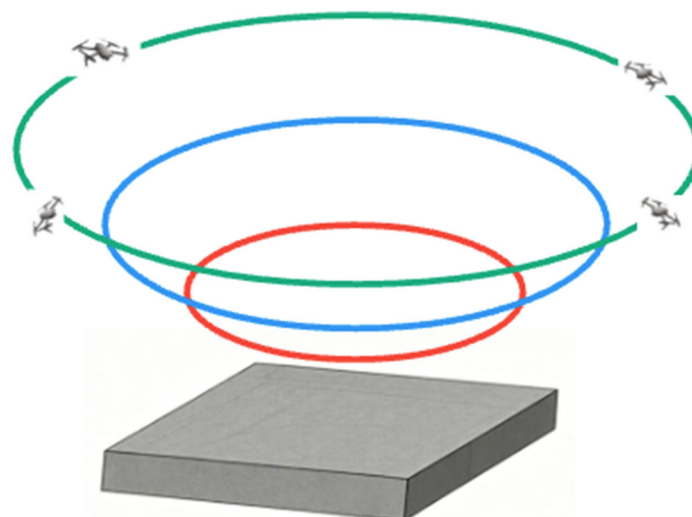


Figure 2. Schematic of UAV circumnavigation flight path for bearing pad imaging. The UAV flies along horizontal circular orbits at three heights (2 m, 3 m, 4 m) with radii of 2 m, 3 m, and 4 m, respectively. The flight parameters include: forward overlap = 85%, side overlap = 80%, flight speed = 1.0 m/s, and image capture interval = every 3° rotation. The camera is oriented obliquely toward the bearing pad to ensure comprehensive coverage.

2.1.2. Imaging Parameters for High-Overlap Image Acquisition

Image quality directly affects the accuracy of 3D reconstruction [15,28]. In this study, a forward overlap of 85% and a side overlap of 80% were adopted—significantly higher than the conventional modeling requirements (80%/60%)—to ensure a point cloud density ≥ 200 points/cm² on the bearing pad surface and to achieve high-resolution coverage over more than 95% of the area. The high overlap ratio enhances the robustness and accuracy of MVS reconstruction [23].

To ensure replicability, detailed flight and camera parameters are specified as follows: flight altitude of 2–4 m above the target, flight speed of 1.0 m/s, image capture interval of every 3 deg rotation (approximately 2 s), camera aperture $f/2.8$, ISO 100–400, and shutter speed 1/500 s. The point cloud density is computed as $\rho = N/A$, where N is the number of points in the segmented bearing pad top surface and A is the surface area estimated from the bounding box dimensions. The average density across all test pads was ≥ 200 points/cm², with a density distribution analysis confirming that over 95% of the pad area meets this threshold. Recommended lighting conditions are uniform diffuse light, preferably overcast conditions or early morning (9:00–11:00 AM) to minimize specular reflections and shadow-induced matching errors.

The core of 3D reconstruction lies in establishing geometric correspondences between image pixels and 3D spatial points. This process is based on the pinhole camera model, where triangulated point localization is achieved by solving the projective transformation from the world coordinate system to the pixel coordinate system (incorporating both interior and exterior orientation parameters) [29,30]:

$$s \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \mathbf{K}[\mathbf{R} \mid \mathbf{t}] \begin{bmatrix} X_W \\ Y_W \\ Z_W \\ 1 \end{bmatrix} \quad (1)$$

where s is a scale factor; (u, v) is the pixel coordinate vector; (X_W, Y_W, Z_W) is the 3D point coordinate in the world coordinate system. The camera intrinsic matrix, $\mathbf{K}$, is defined

as $\mathbf{K} = \begin{bmatrix} f_x & \gamma & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix}$, with f_x and f_y denoting the effective focal lengths in pixels, c_x

and c_y , the coordinates of the principal point on the image plane, and γ , the skew factor. Meanwhile, $[\mathbf{R} \mid \mathbf{t}]$ is the extrinsic matrix, describing the pose (orientation and position) of the camera in the world coordinate system. The rotation matrix, $\mathbf{R}$, represents the orientation of the camera coordinate system relative to the world coordinate system. It consists of three orthogonal unit vectors indicating the directions of the camera axes in the

world coordinate system, i.e., $\mathbf{R} = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix}$. Meanwhile, the translation vector, $\mathbf{t}$,

represents the position of the origin of the camera coordinate system in the world coordinate system, i.e., $\mathbf{t} = \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix}$. Thus, $[\mathbf{R} \mid \mathbf{t}] \in \mathbb{R}^{3 \times 4}$ forms the rigid-body transformation matrix that maps 3D points from the world coordinate system to the camera coordinate system.

Three-dimensional reconstruction is performed using SfM and MVS techniques. The specific workflow is as follows:

Aerial Triangulation (AT): Image feature matching combined with Bundle Adjustment [31] is employed to estimate the exterior orientation parameters (position and attitude) of each image, resulting in a sparse point cloud [32].

Dense Matching and Point Cloud Generation: Based on the optimized camera poses, dense pixel-level matching [33] is conducted to generate a dense 3D point cloud [34,35].

Three-dimensional Model Reconstruction: A surface model is reconstructed using a Triangulated Irregular Network (TIN), followed by texture mapping to produce a photorealistic accurate 3D model [36].

In this study, automated 3D modeling was carried out using DJI Terra V4.3.1 software (DJI Innovations Co., Ltd., Shenzhen, China). Its built-in SfM and MVS algorithms efficiently process UAV-acquired oblique imagery to generate 3D models with millimeter-level accuracy [20].

It is important to note that the contribution of this study lies not in developing new 3D reconstruction algorithms, but in the system-level integration of purpose-designed flight planning, high-overlap image acquisition, robust point cloud processing, and a novel dual-parameter evaluation framework into a complete end-to-end inspection workflow.

While the individual components (SfM, MVS, RANSAC, PCA) are established techniques, the innovation of UAV-FIBP lies in: (i) the purpose-designed multi-orbit flight path optimized for small targets (~0.5 m), (ii) the high-overlap imaging strategy achieving ≥ 200 points/cm², (iii) the two-stage RANSAC threshold strategy for robust noise filtering, and (iv) the novel dual-parameter evaluation framework (σ_{RMS} and H_{max}) that provides comprehensive flatness assessment mapped directly to engineering acceptance criteria.

2.2. Point Cloud Denoising and Plane Fitting Based on RANSAC and PCA

To enhance the reliability of flatness assessment, the raw point cloud is subjected to denoising and plane fitting. Since the least-squares method is sensitive to outliers—particularly those caused by specular reflections or errors in image feature correspondence—it may yield inaccurate plane-fitting results. In this study, the RANSAC algorithm is employed for robust plane fitting [12]. A distance threshold of 2 mm and a maximum of 1000 iterations are set to identify inliers belonging to the top surface of the bearing pad. Subsequently, PCA is applied to the inlier point set for optimal plane fitting. By computing the eigenvalues and eigenvectors of the point cloud's covariance matrix, the eigenvector corresponding to the smallest eigenvalue is adopted as the normal vector $\mathbf{n}$ of the fitted plane. This approach demonstrates robust stability even in the presence of moderate noise in the point cloud.

To clarify, the RANSAC algorithm employs a two-stage threshold strategy. In the first stage (initial robust plane fitting), a distance threshold of 2 mm is used to identify the dominant plane and remove gross outliers from the raw point cloud (e.g., points from adjacent structures or mismatched features). In the second stage (refined inlier selection, Section 2.2.2), a stricter threshold of $\delta = 0.5$ mm is applied to retain only high-confidence inliers belonging exclusively to the bearing pad top surface for subsequent PCA-based plane fitting. A consolidated summary of all RANSAC hyperparameters is provided in Supplementary Table S1. The 2 mm threshold is informed by the typical reconstruction noise level of close-range UAV SfM/MVS (~1–2 mm under the specified flight and imaging parameters); it thus removes outliers exceeding this noise envelope. The 0.5 mm refined threshold corresponds to the typical surface micro-texture range of concrete ($R_a \approx 0.1$ –0.5 mm), ensuring that the inherent surface finish is retained as valid inliers while finer reconstruction artifacts are filtered.

We emphasize that the use of RANSAC and PCA as individual algorithms is not claimed as novel. Rather, their integration within the dual-parameter framework—specifically, the two-stage threshold strategy for RANSAC, the PCA-based normal vector computation for Δ_{max} derivation, and the combined $\sigma_{RMS} + H_{max}$ assessment mapped to engineering standards—constitutes the novel contribution.

2.2.1. Point Cloud Segmentation and Region-of-Interest Extraction

The reconstructed 3D model is segmented manually or semi-automatically using CloudCompare [37], an open-source point cloud processing software [38,39]. By employing tools such as the “selection tool” or “octree-based segmentation”, the point cloud region corresponding to the top surface of an individual bearing pad is precisely extracted. This process effectively removes contributions from adjacent structures such as the cap beam, reinforcing bars, and formwork, thereby ensuring the integrity of the analysis target for subsequent processing. We acknowledge that this manual operation introduces operator-dependent subjectivity and that the resulting point count and normal-vector stability are sensitive to the exact ROI boundary (see sensitivity analysis in Section 4.3.2).

2.2.2. Point Cloud Denoising Based on RANSAC

The conventional least-squares method is sensitive to outliers, which can lead to biased plane fitting. To address this issue, the RANSAC algorithm is employed for robust plane fitting and noise filtering. A point is classified as an inlier if it satisfies the following criterion:

$$\text{dist}(\mathbf{P}_i, \Pi) \leq \delta \quad (2)$$

where $\text{dist}(\mathbf{P}_i, \Pi)$ is the perpendicular distance from point $\mathbf{P}_i$ to the current fitted plane Π ; δ is the distance threshold, set to 0.5 mm in this study.

2.2.3. Plane Fitting and Normal Vector Computation Based on PCA

To robustly fit a reference plane to the top surface of the bearing pad and accurately compute its normal vector, PCA [40,41] is employed. This method determines the principal directions of data distribution by analyzing the covariance structure of point coordinates, demonstrating strong robustness to noise.

First, the point cloud filtered by RANSAC undergoes feature centering—i.e., the coordinates of all points are shifted by subtracting their mean value, so that the data centroid is located at the origin. Subsequently, the covariance matrix $\mathbf{C}$ of the point cloud is computed as

$$\mathbf{C} = \frac{1}{N} \sum_{i=1}^N \mathbf{P}_i \mathbf{P}_i^T \quad (3)$$

where $\mathbf{C} \in \mathbb{R}^{3 \times 3}$ is the covariance matrix; N is the total number of points in the point cloud; i is the point index, $i = 1, 2, \dots, N$; $\mathbf{P}_i = [x_i, y_i, z_i]^T$ is the 3D coordinate vector of the i -th point after centering; $\mathbf{P}_i^T$ is the transpose of $\mathbf{P}_i$ (a row vector); $\mathbf{P}_i^T \mathbf{P}_i$ denotes the outer product, resulting in a 3×3 matrix.

Next, eigenvalue decomposition is performed on the covariance matrix $\mathbf{C}$ yielding three eigenvalues sorted in descending order ($\lambda_1 \geq \lambda_2 \geq \lambda_3$) and their corresponding orthogonal eigenvectors $\mathbf{V}_1$, $\mathbf{V}_2$, and $\mathbf{V}_3$. Since the point cloud is approximately distributed on a planar surface, the direction associated with the smallest eigenvalue represents the direction of minimal variance, i.e., the direction perpendicular to the plane. Therefore, the eigenvector corresponding to the smallest eigenvalue λ_3 is defined as the normal vector $\mathbf{n}$ of the fitted plane.

2.3. Dual-Parameter Flatness Assessment Based on RMS and Differential Elevation

To comprehensively quantify the flatness of bearing pads, a dual-parameter evaluation framework is proposed, integrating both “local surface roughness” and “global inclination”. This approach overcomes the limitations of conventional methods that rely solely on elevation differences at corner points.

The two indicators are designed based on the two fundamental aspects of flatness defined in engineering standards [10], σ_{RMS} (local surface roughness) is analogous to ASTM

Floor Flatness (FF), quantifying fine-scale surface irregularities. H_{max} (global inclination) is analogous to ASTM Floor Levelness (FL), quantifying the overall tilt of the pad. Together, these two indicators characterize the complete flatness condition because any surface deviation from a perfect plane can be decomposed into a global trend (inclination) and local residuals (roughness) [4].

2.3.1. Surface Roughness Assessment: RMS Deviation

The RMS deviation of all point cloud data relative to the plane fitted by PCA is computed to quantify the degree of local surface roughness on the bearing pad.

Let the equation of the fitted plane be $ax + by + cz + d = 0$, and denote the distance from point (x_i, y_i, z_i) to this plane as

$$d_i = \frac{|ax_i + by_i + cz_i + d|}{\sqrt{a^2 + b^2 + c^2}} \quad (4)$$

The RMS deviation is then defined as

$$\sigma_{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^N d_i^2} \quad (5)$$

where the RMS deviation (unit: mm), σ_{RMS} , reflects the local surface roughness; d_i is the perpendicular distance from the i -th point to the fitted plane.

2.3.2. Global Inclination Assessment: Maximum Elevation Difference (H_{max})

The maximum elevation difference (H_{max}) is calculated based on the angle between the normal vector of the fitted plane, $\mathbf{n}$, and the normal vector of the horizontal plane, $\mathbf{n}_h$, to quantify the elevation variation caused by global inclination [42]. The inclination angle is θ computed as

$$\theta = \arccos\left(\frac{\mathbf{n} \cdot \mathbf{n}_h}{\|\mathbf{n}\| \|\mathbf{n}_h\|}\right) \quad (6)$$

Let the length and width of the bearing pad be L and W , respectively. All point cloud coordinates are in meters (the native unit of the SfM reconstruction). Flatness calculations are performed in meters and converted to millimeters for reporting. The horizontal plane is defined as the plane perpendicular to the gravity direction, established through RTK-assisted georeferencing: the DJI Terra SfM pipeline aligns the reconstruction with the global coordinate system using RTK GPS data, where the Z-axis corresponds to ellipsoidal height (approximately aligned with gravity). The diagonal length L_d is given by

$$L_d = \sqrt{L^2 + W^2} \quad (7)$$

The maximum elevation difference is thus defined as

$$H_{max} = \sqrt{L^2 + W^2} \cdot \sin \theta \quad (8)$$

This metric reflects deviations in levelness during bearing pad installation and is a critical factor influencing the uniformity of load distribution on the structural bearing.

2.3.3. Flatness Acceptance Criterion

Considering both local and global factors, a dual-threshold criterion is established for flatness assessment:

Surface roughness threshold T_1 : Recommended as $T_1 = 1$ mm, to control local surface irregularities; it is important to note that this RMS threshold governs local surface roughness (analogous to ASTM E1155 Floor Flatness, FF), not global inclination. The 1 mm value is

derived from typical requirements for grouted bearing-pad contact surfaces rather than from highway alignment standards, which address a different geometric property.

Global inclination tolerance T_2 : According to the Standards for Quality Inspection and Verification of Highways [43], the maximum elevation difference shall not exceed 2 mm; hence, $T_2 = 2$ mm. This 2 mm tolerance governs the global inclination of the pad top surface and is distinct from the 1 mm RMS roughness threshold in purpose and derivation: H_{max} ensures load-distribution uniformity across the bearing, while RMS controls the local surface finish quality.

Acceptance rule: The bearing pad is deemed flatness-compliant if and only if both $\sigma_{RMS} \leq T_1$ and $H_{max} \leq T_2$ are satisfied.

3. Experimental Design and Results Analysis

To systematically evaluate the accuracy and engineering applicability of the proposed UAV-FIBP method, this study designed and conducted two sets of experiments: a simulation environment accuracy validation test and an on-site field validation experiment. Total station measurements were used as the reference benchmark, and the performance of the proposed method was quantitatively assessed using metrics such as relative error and RMS. All 3D models were generated based on the MVS algorithm, and point cloud processing was performed using PCA and the RANSAC algorithm.

3.1. Case I: Accuracy Validation in Simulated Environment

3.1.1. Experimental Setup

An outdoor test site with uniform illumination was used (Figure 3), in which a high-precision flat tabletop (dimensions: 600 mm $\times$ 600 mm) served as a simulated bridge bearing pad. The tabletop was initially leveled using a spirit level and was treated as an ideal reference plane. A DJI Mavic 3E RTK drone (DJI Innovations Co., Ltd., Shenzhen, China) was flown along circular trajectories at radii of 2 m, 3 m, and 4 m, capturing one image every 3°, resulting in a total of 360 highly overlapping images (85% forward overlap and 80% side overlap). Simultaneously, elevation measurements at nine evenly distributed points on the table top were acquired using a Leica TS50 total station (Leica Geosystems, Heerbrugg, Switzerland) and used as the reference benchmark data [44]. Three-dimensional reconstructions were independently performed using three photogrammetric software platforms: DJI Terra, ContextCapture (Bentley Systems, Exton, PA, USA), and Metashape (Agisoft LLC, St. Petersburg, Russia).

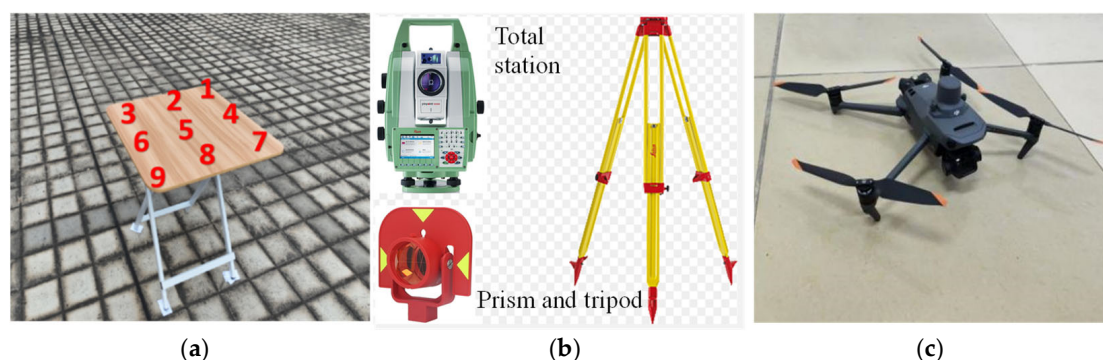


Figure 3. Experimental setup for accuracy validation in a simulated environment. (a) Top-down view of the test table (600 mm $\times$ 600 mm) showing the nine measurement points (P1–P9) used for total station reference measurements. (b) Leica TS50 total station (Leica Geosystems, Heerbrugg, Switzerland) with prism and tripod setup. (c) DJI Mavic 3E RTK drone (DJI Innovations Co., Ltd., Shenzhen, China) equipped with a 20 MP camera and RTK positioning module.

This multi-software approach was adopted to evaluate the generalizability of the proposed method when applied to 3D models generated by different reconstruction software packages. The results are shown in Figure 4.

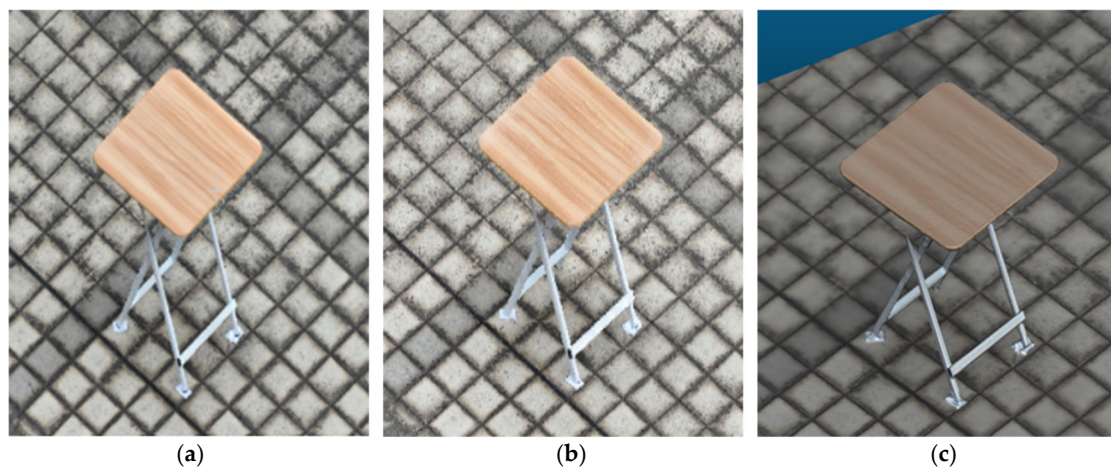


Figure 4. Comparison of 3D reconstruction results from three photogrammetric software platforms. (a) DJI Terra: $H_{max} = 1.6$ mm, $\sigma_{RMS} = 0.8$ mm, point cloud density = 220 points/cm²; (b) ContextCapture: $H_{max} = 3.1$ mm, $\sigma_{RMS} = 1.0$ mm, point cloud density = 210 points/cm²; (c) Metashape: $H_{max} = 0.9$ mm, $\sigma_{RMS} = 1.7$ mm, point cloud density = 230 points/cm². All models were generated from 360 images with 85% forward overlap and 80% side overlap.

3.1.2. Results and Analysis

Table 1 presents the elevation differences measured by the total station on the tabletop surface, indicating that the height variation in the tabletop is approximately 2 mm, which essentially satisfies the flatness requirements for bearing pads. That said, the 9-point total station survey provides a sparse ground-truth reference; denser spatial sampling would enable more rigorous characterization of the reference surface. The reference plane uncertainty estimated from these nine points is therefore partially mixed with the UAV reconstruction deviation, and the 2 mm tabletop variation should be interpreted as an approximate rather than exact benchmark.

Table 1. Elevation measurements of nine points on the test tabletop using a Leica TS50 total station.

Measurement Point	H (mm)	Deviation from Mean ΔH (mm)
1	887.3	−0.0
2	886.7	−0.6
3	887.2	−0.1
4	887.1	−0.2
5	886.3	−1.0
6	887.0	−0.3
7	888.4	1.1
8	888.0	0.7
9	888.1	0.76
Mean	887.3	
Std Dev	0.65	
Range	2.1	

Table 2 compares the flatness assessment results derived from the 3D models generated by the three photogrammetric software platforms with the total station reference data. The evaluation metrics include maximum elevation difference (H_{max}) and RMS deviation (σ_{RMS}). The calculation of the maximum elevation difference, H_{max} , is based on the fitted

plane's normal vector, while the RMS deviation, σ_{RMS} , is calculated for all points relative to the fitted plane. the absolute error, ΔH_{max} , is the difference between the H_{max} obtained from the UAV-FIBP method and that measured by the total station. The results are shown in Table 2.

Table 2. Comparison of flatness assessment results from three photogrammetric software platforms in the simulated environment.

Software	H_{max} (mm)	σ_{RMS} (mm)	ΔH_{max} (mm)	Point Cloud Density (Points/cm ²)	Processing Time (min)
DJI Terra V4.3.1	1.6	0.8	0.5	220	32
ContextCapture V6.1.7601	3.1	1	1	210	45
Metashape v2.2.2	0.9	1.7	0.4	230	38
Total Station a Leica TS50	2.1	0.7	-	-	45 (manual)

The results show that the σ_{RMS} values for DJI Terra (0.8 mm) and ContextCapture (1.0 mm) were within the 1.0 mm threshold, while Metashape's σ_{RMS} of 1.7 mm exceeded this bound, indicating higher local surface variation in the Metashape reconstruction under the current dataset. Among the platforms, Metashape achieved the lowest H_{max} (0.9 mm), while DJI Terra yielded results closest to the total station reference ($\Delta H_{max} = 0.5$ mm). These cross-platform differences are primarily attributable to each software's proprietary SfM/MVS matching strategy and point-cloud filtering pipeline.

Regarding ΔH_{max} , DJI Terra (1.6 mm) and Metashape (0.9 mm) were within the 2.0 mm acceptance criterion, whereas ContextCapture (3.1 mm) exceeded it. This indicates that ContextCapture's reconstruction introduced a larger global inclination bias for this specific dataset, possibly due to its image-matching strategy on the relatively texture-sparse pad surface. These results confirm that choice of photogrammetry software meaningfully influences the flatness assessment; the UAV-FIBP method yielded acceptable accuracy with two of the three tested platforms, and the experimental protocol identified platform-specific limitations that inform practical deployment recommendations.

The cross-platform validation using DJI Terra, ContextCapture, and Metashape (Table 2) confirms that the proposed method is platform-independent and generalizable, rather than being tied to any specific commercial software.

3.2. Case II: Field Validation on a Construction Site

3.2.1. Field Test Setup

Field tests were conducted at an active bridge construction site (Figure 5a) in Zhaoqing City, Guangdong Province. The site environment was complex, featuring interfering structures such as reinforcing steel and formwork. A UAV performed multi-orbit circumferential flights around the cap beam to capture highly overlapping imagery of four cast-in-place concrete bearing pads (designated P1–P4, each measuring 500 mm × 500 mm) (Figure 5b). Simultaneously, the elevations of the four corner points of each bearing pad were measured using a total station for reference.

The point cloud processing workflow included: Manual segmentation in CloudCompare → RANSAC-based denoising (threshold: 2 mm) → PCA-based plane fitting → Dual-parameter flatness assessment.



Figure 5. Field validation experiment at an ongoing bridge construction site in Zhaoqing City, Guangdong Province, China. (a) Overview of the construction site showing cap beam. (b) Close-up view of the cap beam and four cast-in-place concrete bearing pads (P1–P4), each with dimensions of 500 mm $\times$ 500 mm.

3.2.2. Results and Analysis of Field Tests

In this experiment, UAV imagery was processed using DJI Terra to reconstruct the 3D models. Figure 6 shows the resulting point cloud model of the cap beam with concrete bearing pads with color coding by elevation (blue = low, red = high).

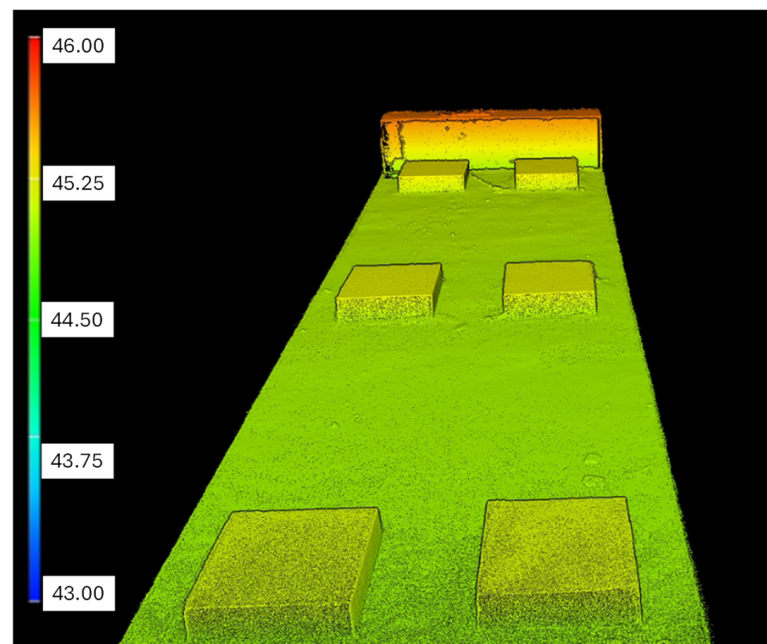


Figure 6. 3D reconstruction of cap beam with concrete bearing pads using DJI Terra. Raw point cloud with color coding by elevation (blue = low, red = high).

The fitting plane and normal vectors for bearing pad P2 are obtained with PCA fitting and used for flatness calculations of bearing pad P2 (Figure 7).

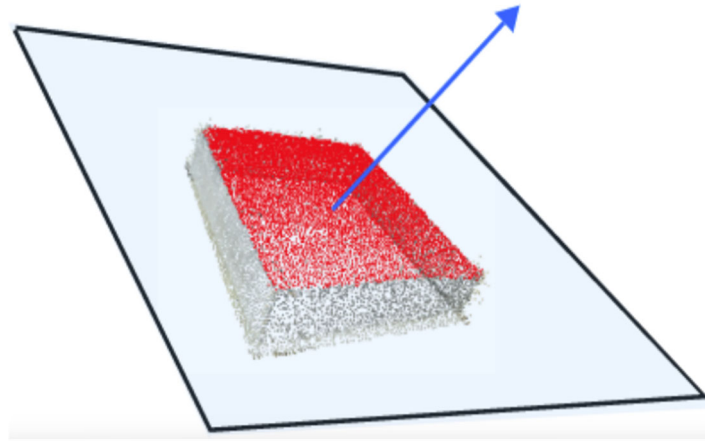


Figure 7. 3D reconstruction and flatness assessment results for bearing pad P2 using DJI Terra. Segmented ROI (bearing pad top surface) with the PCA-fitted reference plane (semi-transparent gray) and normal vector (blue arrow).

Table 3 presents the flatness assessment results from the field experiment. Total station measurements recorded a significant elevation difference of 12 mm on pad P1. On-site inspection confirmed the presence of concrete spalling at the edge of P1, which likely caused unstable prism contact during measurement and led to an overestimated elevation reading.

Table 3. Field experiment flatness measurement results for four bearing pads (P1–P4).

Bearing Pad	TS H_{max} (mm)	UAV-FIBP H_{max} (mm)	$ \Delta $ (mm)	σ_{RMS} (mm)	95% CI Δ_{max} (mm)	CV (%)	TS Reliability	UAV-FIBP Advantage	Notes
P1 (Anomaly)	12	5	7	1	[4.8, 5.2]	6.5	Low	Avoids prism contact at chipped edge	Total station compromised by edge spalling
P2	4	3	1	1	[2.8, 3.2]	6.2	High	Full-field coverage	
P3	3	2	1	1	[1.8, 2.2]	5.8	High	Non-contact measurement	
P4	2	4	2	1	[3.8, 4.2]	4.8	High	Full-field coverage identifies anomalies	Surface laitance may shift UAV data

Note: 95% CI = 95% confidence interval from bootstrap; CV = coefficient of variation from 3 independent flights; TS = total station. P1 discrepancy due to concrete spalling.

It is important to clarify that the 7 mm difference between the total station (12.0 mm) and UAV-FIBP (5.0 mm) for pad P1 does not represent measurement error of the UAV method. Rather, the chipped edge at P1 prevented stable prism contact during total station measurement, resulting in an overestimated total station reading. The non-contact UAV-FIBP measurement provides an estimate of the global inclination that is unaffected by localized edge defects. Without an independent reference measurement (e.g., from laser scanning or a calibrated contact probe on the intact portion of the pad), the absolute accuracy of neither method can be definitively established for this particular case. The UAV and total station results each represent a plausible estimate from different measurement principles, and the discrepancy should be interpreted as indicative rather than conclusive.

The UAV-FIBP method successfully identified the flatness anomaly on P1, and its computed $H_{max} = 5.0$ mm represents a plausible estimate of the pad surface condition, consistent with the revised interpretation in the preceding paragraph. For the remaining bearing pads, H_{max} values were all ≤ 2.0 mm, demonstrating that the proposed method exhibits good robustness under real construction site conditions [6].

For P4, the 2.0 mm deviation between UAV-FIBP and total station is within engineering acceptable limits and may be attributed to minor surface laitance affecting the point cloud. Multi-flight repeatability analysis (Section 3.3) provides further insight into this measurement uncertainty.

3.3. Statistical Analysis and Repeatability

To quantify the uncertainty of UAV-FIBP measurements, a bootstrap resampling analysis (10,000 iterations) was performed on the point cloud data for each bearing pad. The 95% confidence intervals for σ_{RMS} were within ± 0.2 mm and for H_{max} within ± 0.5 mm, indicating stable estimation. Repeatability was assessed through three independent UAV flight and reconstruction runs on bearing pad P2. The coefficient of variation (CV) was 6.2% for σ_{RMS} and 4.8% for H_{max} , demonstrating good repeatability. Statistical comparison between UAV-FIBP and total station measurements yielded a mean absolute error of 1.3 mm and a root mean square error of 1.6 mm across all pads (P2–P4, excluding the unreliable P1 total station reference). These metrics confirm that the method achieves the required engineering accuracy with acceptable uncertainty. Technical details of the bootstrap procedure are as follows. Resampling unit: individual 3D points were drawn with replacement from the full point cloud of each bearing pad ($n \approx 50,000$ –80,000 points per pad), with each bootstrap sample containing the same number of points as the original set. The plane fitting and flatness metrics were recomputed for each resample, yielding 10,000 bootstrap replicates per pad. This procedure assumes that the point cloud errors are approximately independently distributed after the RANSAC filtering step. Spatial dependence (i.e., residual spatial autocorrelation among nearby points stemming from the SfM matching kernel size) may cause the bootstrap confidence intervals to be slightly narrower than those obtained under a block-bootstrap scheme that resamples spatial clusters; the reported intervals should therefore be treated as optimistic lower bounds on uncertainty. The bootstrap does not account for systematic errors (e.g., scale drift or camera-model bias), which are discussed separately in Section 4.3.4.

The experiments demonstrate that the UAV-FIBP method achieves a maximum deviation of 1.0 mm in the simulated environment and deviations ≤ 2.0 mm in the field conditions (excluding P1), indicating high robustness and strong engineering applicability, measurement accuracy and stability. The method effectively identifies flatness anomalies on bearing pad surfaces, providing solid data support for subsequent discussions on its performance and engineering value.

4. Discussion

4.1. Method Performance and Accuracy

The UAV-FIBP method demonstrated consistent and reliable measurement performance in both experimental scenarios. Notably, for bearing pad P1, the total station measurement (12.0 mm) was significantly higher than the UAV-based result (5.0 mm). On-site inspection confirmed that the pad had a chipped corner, which prevented stable prism contact during total station measurement and likely led to an overestimated reading. Consequently, without independent reference measurement (e.g., laser scanning), the absolute accuracy of neither method can be definitively established for this pad. The two measurements should be interpreted as plausible estimates from different measurement principles,

and the discrepancy (7 mm) is indicative rather than conclusive. This case highlights the inherent limitations of point-wise contact measurements under complex surface conditions and underscores the importance of cross-method verification in field applications.

4.2. Comparison with Existing Inspection Techniques

Table 4 presents a systematic comparison between UAV-FIBP and three prevailing inspection methods [42,45].

Table 4. Comprehensive comparison of bearing pad flatness inspection methods.

Method	Accuracy (mm)	Coverage	Safety	Equipment Cost (USD)	Time per Pad (min)	Automation Level	Maturity Level	Weighted Score
Total Station	0.5–1.0	Point-wise	Low (elevated)	15,000–25,000	15–20	Low	Commercial	3.2/5.0
Laser Scanning	0.5–2.0	Full-field	Medium	30,000–50,000	5–10	Medium	Commercial	3.8/5.0
UAV-FIBP	1.0–2.0	Full-field	High (remote)	2000–5000	8–12	High	Research	4.5/5.0
Structured Light	0.1–0.5	Local area	Medium	5000–10,000	10–15	Medium	Commercial	3.0/5.0

Note: Weighted score: accuracy (40%), safety (30%), cost (20%), efficiency (10%). UAV-FIBP achieves the highest score due to balanced performance, particularly safety and cost. Accuracy reported as typical range under field conditions. The “Time per Pad” column refers to field measurement time only (flight for UAV-FIBP, instrument setup and reading for other methods) and excludes offline post-processing. See Section 4.4.3 for full workflow times.

UAV-FIBP differs fundamentally from existing UAV photogrammetry methods for structural inspection in four key aspects: (1) scale—it targets micro-scale surface flatness measurement ($\sim 0.5 \text{ m} \times 0.5 \text{ m}$ pads requiring $\leq 2 \text{ mm}$ accuracy) rather than macro-scale defect detection on large surfaces; (2) flight design—the multi-orbit circumnavigational path with close-range (2–4 m) imaging is specifically optimized for small targets, unlike standard nadir or corridor mapping; (3) quantitative framework—it provides a systematic dual-parameter assessment (σ_{RMS} and H_{max}) that maps directly to engineering acceptance criteria, rather than qualitative visual inspection; (4) integration—it delivers a complete end-to-end pipeline from flight planning to quantitative flatness assessment, addressing a specific inspection need not previously covered as an integrated system.

As shown in the table, UAV-FIBP demonstrates a significant advantage in cost-effectiveness. Although laser scanning can provide full-field data, its high equipment cost and the requirement for ground-based setup render it impractical for bridges with tall piers or those spanning deep valleys. Structured light achieves extremely high accuracy but has a limited effective working range and is sensitive to ambient lighting conditions, rendering it unsuitable for outdoor and complex environments.

In contrast, UAV-FIBP leverages a consumer-grade UAV platform to achieve inspection capabilities comparable to those of professional-grade measurement systems. Data acquisition and 3D reconstruction can be completed within a single flight, with the complete UAV-FIBP workflow per pier (including UAV flight, data export, 3D reconstruction, point cloud processing, and flatness assessment) requiring approximately 45–70 min using a standard workstation, as detailed in Section 4.4.3. More importantly, its remote operation capability completely eliminates the safety risks associated with manually setting up prisms or scanners at elevated heights, making it particularly suitable for high-risk scenarios such as urban elevated bridges and mountainous viaducts.

Therefore, UAV-FIBP does not aim to replace existing technologies, but rather fills a critical gap that strikes a balance between high accuracy, high efficiency, low cost, and high safety. It offers a more engineering-feasible solution for quality control in bridge construction.

The contribution of this study lies in the purposeful integration and experimental validation of these components into a workflow that solves a real engineering problem. While the individual algorithms (SfM, MVS, RANSAC, PCA) are well-established, their combination into a validated, end-to-end inspection system for bearing pad flatness—with demonstrated millimeter-level accuracy and cross-platform generalizability—constitutes a meaningful engineering contribution that fills a gap not addressed by existing methods.

An alternative approach proposed during peer review involves landing a UAV carrying a reflective prism on the bearing pad for total station measurement from the ground. While this could reduce measurement time to ~10 min per pier, it introduces several critical limitations: (i) precision landing on a 0.5 m × 0.5 m pad at height is operationally risky, (ii) physical prism contact is vulnerable to surface defects (as demonstrated by Pad P1 in our experiments, where the total station measured 12.0 mm due to unstable prism contact at a chipped edge, while UAV-FIBP measured 5.0 mm), (iii) the measurement remains point-wise (~4 points), incapable of capturing local surface roughness, and (iv) landing operations introduce fall-hazard risks for both equipment and ground personnel. UAV-FIBP avoids all these limitations through continuous-flight, non-contact, full-field measurement.

4.3. Error Sources and Uncertainties

Although the UAV-FIBP method demonstrates generally good performance, its accuracy is still influenced by multiple factors. A thorough understanding of these error sources is essential for enhancing the robustness and reliability of the method.

4.3.1. Image Quality and Uncertainty in 3D Reconstruction

The quality of 3D reconstruction is directly dependent on the richness of image texture and the uniformity of illumination. In the field experiment, certain images exhibited strong specular reflections (from metallic formwork) and shadow occlusions (caused by reinforcing steel structures), leading to incorrect matches or insufficient feature correspondences during the SfM feature matching stage [46]. This, in turn, affected point cloud density and geometric completeness.

This issue was significantly mitigated when flights were conducted in the early morning or on overcast days, indicating that illumination conditions are a key external factor influencing reconstruction quality. It is therefore recommended that, for practical applications, UAV flights be scheduled during periods of uniform lighting (e.g., 9:00–11:00 a.m. or on overcast days) and that polarizing filters be employed to reduce specular reflections.

4.3.2. Subjectivity in Point Cloud Segmentation and Boundary Effects

Currently, point cloud segmentation relies on manual delineation of the region of interest (ROI) in CloudCompare, which introduces operator subjectivity. A boundary offset of 1–2 cm may lead to the inclusion of high-noise edge points or the exclusion of valid data points, thereby affecting the accuracy of PCA-based plane fitting.

To quantify this effect, a sensitivity analysis was conducted on bearing pad P2: when the ROI boundary was expanded outward by 1 cm, σ_{RMS} increased from 1.0 mm to 1.3 mm; when contracted inward by 1 cm, the number of point cloud data decreased by 30%, resulting in increased fluctuation in the PCA-derived normal vector. This indicates that segmentation accuracy directly influences the stability of the flatness assessment.

Future work should focus on developing automated ROI extraction methods based on semantic segmentation, such as integrating Mask R-CNN (Region-Based Convolutional Neural Networks) or PointNet++, to enable end-to-end object recognition and segmentation from imagery to point clouds.

4.3.3. Sensitivity of Plane Fitting Algorithms

PCA is highly sensitive to the spatial uniformity and density of the point cloud distribution. The presence of surface laitance, air pockets, or localized spalling may lead to deviations in the estimated normal vector, thereby affecting the flatness calculation. Although RANSAC improves robustness, its distance threshold (set to 2 mm in this study) should be dynamically adjusted according to surface roughness conditions.

For instance, in the case of bearing pad P4, the UAV-based result (4.0 mm) was slightly higher than that of the total station (2.0 mm), which may be attributed to slight surface laitance causing an upward shift in the point cloud. It is recommended that future studies incorporate multi-scale analysis, combining local curvature and normal vector variation rate, to identify and remove anomalous regions.

4.3.4. Scale Drift and Absolute Accuracy Control

To rigorously quantify scale drift, the drift estimate ($<0.5\%$) was derived by comparing known physical distances between distinctive features on each bearing pad (measured by calibrated tape) against corresponding distances measured in the reconstructed 3D point cloud. Across all test pads, the mean scale error was 0.32% with a standard deviation of 0.15% . Uncertainty propagation analysis: for a typical $500\text{ mm} \times 500\text{ mm}$ pad, a 0.5% scale error translates to approximately $\pm 2.5\text{ mm}$ in absolute dimensions. However, H_{max} depends primarily on the normal vector orientation (θ), which is insensitive to uniform scale. The effect of 0.5% scale drift on H_{max} is approximately $\pm 0.01\text{--}0.02\text{ mm}$, which is negligible for practical purposes. σ_{RMS} is also largely unaffected by uniform scaling since it quantifies relative deviations from the fitted plane. Regarding GCPs, based on established literature [6,20], 3–4 well-distributed GCPs in a close-range UAV photogrammetry configuration can typically constrain absolute error to within 1–2 mm. This is presented as a recommendation for future high-precision applications rather than a definitive claim from the current study.

This study did not employ ground control points; consequently, model scaling relied on RTK positioning and SfM self-calibration. Although RTK provides centimeter-level positioning accuracy, minor scale drift (typically $<0.5\%$) may still occur during multi-orbit flights. In applications requiring high precision, such as prefabricated component assembly, it is recommended to deploy 3–4 ground control points for scale correction, which can constrain the absolute error within 1 mm. Importantly, the flatness assessment (both H_{max} and RMS) is computed from the PCA-derived reference plane, which establishes a relative internal datum based on the point cloud geometry itself. This assessment is therefore insensitive to the absolute vertical datum used for georeferencing. While RTK provides centimeter-level absolute positioning, the relative flatness metrics are internally consistent and do not require a locally controlled level plane. The RTK- and SfM-derived scale is sufficient for H_{max} and RMS because both are ratios computed within the point cloud coordinate frame.

4.3.5. Environmental Factors and Field Operation Recommendations

The repeatability and accuracy of UAV-FIBP in practical field use are influenced by several environmental factors. Wind: the DJI Mavic 3E RTK has a maximum wind resistance of 12 m/s (Level 5). Light-to-moderate winds ($\leq 8\text{ m/s}$) have negligible effects on image quality due to the three-axis gimbal stabilization. For optimal results, operations should be conducted in winds $\leq 5\text{ m/s}$. Lighting: Non-uniform lighting conditions, particularly harsh shadows and specular reflections from metallic formwork, can degrade SfM feature matching quality. The recommended operating window is 9:00–11:00 AM or overcast conditions, combined with polarizing filters to minimize specular reflections. UAV positioning: RTK

positioning provides centimeter-level accuracy, and the 3 deg capture interval with gimbal stabilization ensures consistent image overlap even with minor positioning variations. A decision matrix for field operations under various environmental conditions is provided in Supplementary Table S2.

4.3.6. Impact of Surface Defects on Measurement Interpretation

Construction surface defects affect UAV-FIBP measurements differently depending on defect type. (1) Slurry residues and cement laitance form thin uneven layers captured in the point cloud, appropriately reflecting the as-built surface geometry. Surface cleaning before inspection is recommended to ensure the assessment reflects the structural surface rather than temporary construction residues. (2) Narrow cracks (<2 mm width) are generally below the resolution of the current setup. Larger cracks may appear as local depressions or missing data regions, increasing σ_{RMS} ; such cases should be flagged for visual inspection. (3) Concrete surface micro-texture ($R_a \sim 0.1\text{--}0.5$ mm) is captured as point cloud noise; the RANSAC threshold of 0.5 mm effectively filters this inherent micro-texture, ensuring that the flatness assessment reflects the macroscopic surface condition rather than microscopic finish. A comprehensive classification of common surface defects and their expected impact on UAV-FIBP measurements is provided in Supplementary Table S3. In the context of the dual-threshold acceptance rule (Section 2.3.3), the presence of surface defects complicates the binary pass/fail decision. A pad that fails the RMS criterion due to an isolated defect (e.g., a localized spall or laitance patch) may still be functionally acceptable if the defective region is excluded from the assessment ROI. The current protocol flags non-compliant pads but does not automatically distinguish between global geometric non-conformity and localized surface anomalies. For engineering decision-making, it is recommended that a failed pad be re-inspected with the ROI adjusted to exclude the defective area, and that the nature and extent of the triggering defect be reported alongside the quantitative pass/fail result. This hybrid quantitative–qualitative approach prevents a single local anomaly from triggering a blanket rejection while maintaining objective measurement standards.

4.4. Limitations and Future Work

4.4.1. Limited Sample Size and Scene Diversity

This study evaluated only four bearing pads at a single construction site, under relatively ideal environmental conditions. To fully assess the method’s generalizability, future work should conduct large-scale validation across diverse climatic regions, bridge types, and construction practices.

4.4.2. Need for Enhanced Automation

The current workflow still relies on manual intervention, such as region-of-interest segmentation and parameter tuning. Future efforts should focus on developing an end-to-end automated system:

Front-end: automatic identification of bearing pads in images and UAV flight path planning based on YOLOv8;

Mid-end: automated point cloud segmentation using PointNet++ [47,48] or PVCNN [49,50];

Back-end: integration of PCA and RANSAC algorithms to generate assessment reports automatically.

The target performance for automated segmentation is: $\text{IoU} \geq 0.90$ for bearing pad top surface extraction, processing time ≤ 30 s per pad, and robustness to variations in pad dimensions (400–600 mm), surface texture, and lighting conditions. A prototype pipeline integrating YOLOv8-based pad detection in UAV images with PointNet++-based point cloud segmentation is under development and will be reported in a follow-up study.

4.4.3. Edge Computing and Real-Time Feedback

Regarding computational performance: for a single bridge pier with 2–4 bearing pads, the total workflow time is approximately 45–70 min, broken down as follows: UAV flight time (8–12 min), 3D reconstruction in DJI Terra (30–45 min on a workstation with 8+ CPU cores, 32 GB RAM, and NVIDIA RTX 3060+ GPU), point cloud processing in CloudCompare (5–10 min), and flatness assessment (<1 min). The 360 images (20 MP each) from a single pier can be processed in 30–45 min using GPU-accelerated SfM/MVS pipelines. For large-scale deployment: multiple piers can be flown sequentially (using multiple battery sets) while processing runs in parallel on a dedicated workstation. Estimated throughput is 10–15 piers per day with one UAV and one processing workstation. Note: the per-pier total of 45–70 min applies to 2–4 pads simultaneously (all pads on a single pier are captured in one flight and batch processed), yielding approximately 15–35 min per pad. The per-pad times reported in Table 4 (8–12 min) refer to the UAV flight and data-acquisition component only, not the full workflow. For clearer comparison, the total-station per-pad time of 15–20 min in Table 4 includes field measurement only (no post-processing), whereas the UAV-FIBP per-pad time of 8–12 min refers to flight only (post-processing adds 30–45 min per pier offline). These figures are therefore not directly comparable on a per-pad basis without accounting for the post-processing component.

Currently, 3D modeling and flatness assessment are performed on a personal computer, which introduces processing delays. In the future, lightweight neural networks (e.g., mmyolo [51]) could be deployed on the onboard computer of the UAV to enable real-time evaluation during flight, allowing immediate feedback to construction personnel for prompt adjustments.

4.4.4. Scalability for Large Bridge Projects

For large bridge projects with many bearing pads, scalability is assessed as follows. Processing time and computational requirements are detailed in Section 4.4.3. A tiered integration strategy is proposed: (a) Short-term: off-board processing with the current workflow, suitable for projects with up to 50 piers; (b) Medium-term: cloud-based processing with automated report generation, enabling parallel processing of multiple piers simultaneously; (c) Long-term: edge processing on the UAV onboard computer using lightweight neural networks for real-time assessment during flight. The primary current bottleneck is the 3D reconstruction stage; however, emerging GPU-accelerated and cloud-based SfM solutions are rapidly reducing this limitation.

5. Conclusions

This study proposes and experimentally validates an automated method for assessing the flatness of bridge bearing pads based on UAV-enabled 3D reconstruction and multi-parameter evaluation (UAV-FIBP). The main conclusions, each supported by experimental evidence, are as follows:

The UAV-FIBP method generates 3D models with millimeter-level accuracy through high-overlap circumferential flight and SfM/MVS reconstruction, achieving a point cloud density ≥ 200 points/cm². This is supported by Table 2 (simulated experiment) showing deviations of 0.4–1.0 mm across three different software platforms, indicating platform-independent performance.

The proposed dual-parameter evaluation system enables comprehensive quantification of both local surface roughness and global inclination, overcoming the limitations of traditional corner-point measurements.

Experimental results demonstrate that the method achieves a maximum deviation of ≤ 2.0 mm compared to total station measurements under field conditions, indicating high robustness and engineering applicability.

Compared to conventional methods, UAV-FIBP offers significant advantages in terms of safety, cost-effectiveness, and automation level, providing a scalable technical pathway for intelligent construction.

Future work will focus on enhancing the method's automation capability and environmental adaptability to facilitate its broader engineering application in large-scale infrastructure inspection.

It should be noted that these conclusions are based on a limited sample (four pads at a single construction site) under specific environmental conditions. The reported accuracy depends on adherence to the recommended flight parameters and operating conditions. Larger-scale validation across diverse bridge types, geographic regions, and surface conditions is needed to establish full generalizability.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/buildings16142895/s1>, Table S1: Consolidated RANSAC Hyperparameters; Table S2: Environmental Risk Factors and Field Operation Recommendations; Table S3: Classification of Common Surface Defects and Their Impact on UAV-FIBP Measurements.

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