

Article

Advanced Computer Vision Technology for Real-Time Rotation Angle Monitoring of Bridge Bearings in Structural Health Assessment

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Abstract

Real-time perception of bearing rotation angles is essential for structural health assessment of bridges. However, existing vision-based rotation angle measurement methods exhibit limited robustness to time-varying operational conditions and tracking errors, particularly in practical applications of bridge monitoring. To address this limitation, this study presents an advanced computer vision-based monitoring technology for bridge bearing rotation angles by incorporating specifically configured retroreflective targets, an efficient target tracking approach, and a rotation angle calculation algorithm. Firstly, under LED illumination, retroreflective targets appear as bright, high-contrast features in the images, facilitating precise detection and tracking. Secondly, target centroids are tracked with sub-pixel accuracy through thresholding, edge extraction, and ellipse fitting. Lastly, the bearing rotation angle is calculated by analyzing the angle between the two characteristic lines formed by the target centroids. To validate the effectiveness of the proposed method, comprehensive numerical investigations were conducted, and the results showed that the proposed method maintained high accuracy across various imaging conditions. Additionally, comparative analysis with an existing advanced method also revealed that the proposed method exhibits superior measurement performance even under target tracking uncertainties. To investigate its feasibility and validate its practical effectiveness, a field application on an 80 m + 80 m continuous beam was conducted, and minute rotation angle measurements during 23 railway train drive-by events were obtained using the proposed method, yielding a root mean square error of 0.0008° and mean absolute error of 0.0007°. The successful development and field deployment demonstrate significant potential for advancing structural health monitoring technologies, contributing to intelligent infrastructure management through automated monitoring and early warning capabilities.

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Keywords: bridge bearing; rotation angle measurement; computer vision sensing technique; non-contact monitoring; structural health monitoring

1. Introduction

Bridge bearings serve as key structural components that transfer bridge deck loads to piers while accommodating rotations induced by temperature variations and traffic loading. In this situation, accurate measurement of bearing rotation angles is essential for assessing bridge health conditions [1,2], detecting abnormal bearing behavior [3], and preventing potential safety hazards [4]. Traditional bearing rotation monitoring primarily relies on contact-type instrumentation [5]. Gravity-based inclinometers measure rotation angles through the comparison with the gravitational vertical reference [6]. Displacement sensors (such as displacement gauges) calculate rotation angles from the difference of displacement at spatially separated positions [7]. However, these contact-type methods require direct physical installation on bearing surfaces, presenting significant practical challenges such as installation complexity [8], potential interference with structural behavior [9], low testing efficiency [10], and high maintenance requirements for long-term monitoring [11]. These limitations have motivated the development of non-contact measurement approaches for bridge bearing rotation monitoring.

Computer vision-based sensing and measurement technology provides a promising non-contact alternative for bridge health monitoring [12,13]. Benefiting from its distinct advantages such as easy operation [14] and simultaneous multi-point monitoring capability [15], computer vision-based technology has been widely applied to the displacement measurement in bridge health monitoring [16,17]. Ghaychi Afrouz [18] used close-range photogrammetry technology to achieve dynamic displacement measurement of structures. Wu [19] developed an optical flow displacement measurement method to address challenges in accurately measuring cable displacement under small displacement conditions and mitigating background interference in complex environments. In addition, Liu [20] proposes a novel mutually guided tracking method to address the problem of inaccurate tracking due to the partial occlusion, achieving sub-millimeter displacement measurement of the structure. Shi [21] utilized the template matching method to achieve the displacement measurement for the incremental launching construction of the Yongning Bridge. Xiu [22] established a Kalman filtering-based displacement estimation method by fusing acceleration data with vision-based measurement results, thereby improving the high-frequency vibration information of existing vision-based methods. The above studies demonstrate the promising potential of vision-based technologies for bridge displacement monitoring.

In addition to displacement measurement, computer vision technology also has the potential to realize rotation angle measurement for different kinds of structures. Cheng [23] proposed a rotation angle measurement method based on machine vision techniques with linear features, achieving an accuracy exceeding 3" within $\pm 1^\circ$ through laboratory verification for a rotor machine. Nevertheless, this approach depends on numerous parameters that must be preset, such as gradient magnitude thresholds, which makes it suitable only for fixed mechanical scenarios, hindering its adaptation to bridge monitoring with varying conditions. Lee et al. [24] utilized multiple cameras and image processing techniques to measure the rotation of a high-rise building structure. Nevertheless, the use of multiple cameras substantially increases the equipment investment and the complexity of identification. Park and Artese et al. [25,26] proposed a rotation measurement method for a beam end using a low-cost laser pointer and camera. However, the method is susceptible to the interference of environmental motion, as even slight laser pose variations

can cause dramatic measurement errors. To sum up, the aforementioned methods face significant challenges for practical bridge health monitoring applications due to insufficient environmental robustness and substantial equipment costs.

In recent years, the Perspective-n-Point (PnP)-based technique, which uses spatial constraints of feature points, has also been regarded as one of the most prevalent vision-based methods to realize the effective measurement of bridge bearing rotation. For example, Su et al. [27] developed a real-time simultaneous measurement method of bridge bearing displacement and rotation to realize round-the-clock structure monitoring based on the PnP method. Nevertheless, this method relies on PnP-based camera intrinsic matrix estimation, which suffers from insufficient robustness under real-world operational conditions. Hong [28] also employed the PnP method to measure rotation angles of bridge bearings by estimating the six degrees of freedom (6 DOFs) of markers. However, this method requires high-precision three-dimensional targets. In addition, similar to [27], this method exhibits limited robustness in practical applications. In summary, the primary limitation of PnP-based approaches is their high sensitivity to pixel tracking errors, which stems from stringent calibration requirements. Under non-ideal calibration scenarios, even minor pixel tracking errors can lead to significant measurement inaccuracies. Unfortunately, only limited calibration conditions can be provided at the bridge monitoring sites, thus inevitably lead to inadequate satisfaction for the strict calibration requirements, ultimately resulting in unsatisfactory angle measurement accuracy.

In practical bridge bearing monitoring, systems frequently operate under time-varying conditions [29,30] induced by vehicular vibrations [31] and significant wind loading [32]. These dynamic negative influences make it necessary for the stringent robustness and stability requirements of measurement methodologies. Additionally, spatial constraints at monitoring sites typically permit only limited calibration capabilities, necessitating high tolerance to pixel tracking errors. Current rotation angle measurement techniques, however, demonstrate insufficient robustness for bridge bearing applications, exhibiting vulnerabilities to either environmental variability or pixel tracking uncertainties. To attempt to address these limitations, a novel robust rotation angle monitoring method was proposed in this study by incorporating the specifically configured targets, a target tracking approach, and a rotation angle calculation algorithm. The method achieves enhanced robustness against both environmental variations and pixel tracking errors through synergistic interaction between specialized targets and customized algorithms. In addition, its effectiveness and feasibility were validated by the numerical analysis and on-site experimental investigation.

This paper was organized as follows: Section 2 introduces the theoretical principle and the processing procedure of the proposed method. In Section 3, a series of simulated validations with different shooting conditions is investigated to fully examine the ideal performance of the proposed method. Section 4 presents a comparative analysis between the proposed method and the other existing rotation angle measurement approaches. Section 5 validates the effectiveness and applicability of the proposed method through the field application of bearing rotation monitoring in a real bridge under real environmental conditions. In Section 6, a detailed discussion about the proposed method is presented. Finally, the conclusions are presented in Section 7.

2. Methodology

2.1. Overview of the Proposed Method

The proposed method consists of four specifically configured targets, a target tracking approach, and a rotation angle calculation algorithm. The schematic diagram of the proposed method is shown in Figure 1. Four specifically configured targets were mounted on the bridge bearings. A shooting instrument was employed to capture image data before

and after bridge rotation. The target tracking method was then used to track the center positions of the targets. Finally, the rotation angle calculation method was applied to determine the bridge rotation angle by analyzing the variation of the centerline.

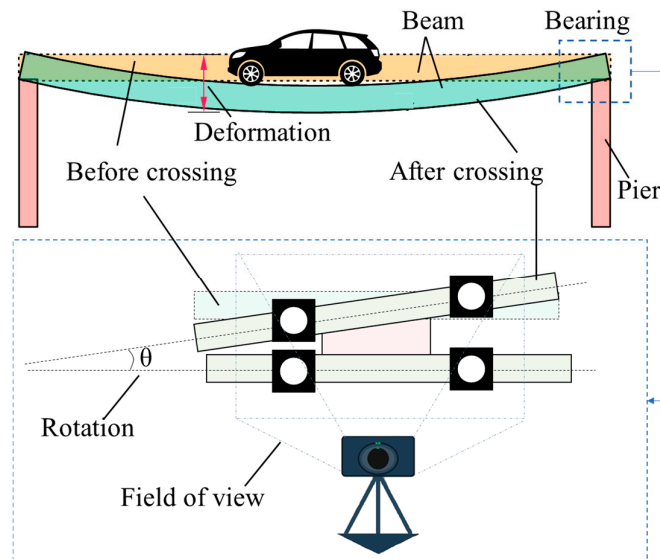


Figure 1. The schematic diagram of the proposed method.

The procedure of the proposed rotation angle monitoring method is shown in Figure 2. Firstly, retroreflective targets are set on the bridge bearings, with two targets on the upper plate and two on the lower plate. Secondly, the imaging system, comprising a camera and the LED lighting, will be installed in front of the targets, so as to acquire image data with high quality. Under LED illumination, the targets will represent bright, high-contrast features in the images, facilitating precise detection and tracking. Thirdly, target centroids are tracked with sub-pixel accuracy through grayscale binarization, edge extraction, and ellipse fitting. Lastly, the bearing rotation angle is obtained by analyzing the angle between the two characteristic lines formed by the target centroids. The specifics of these three steps are presented in Sections 2.2–2.4.

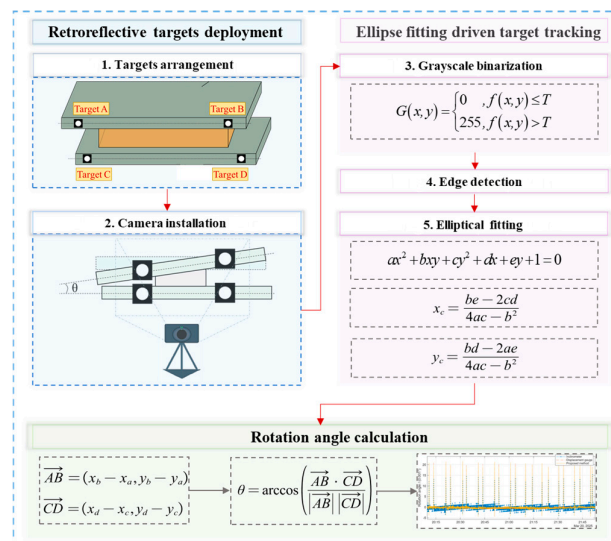


Figure 2. The procedure of the proposed rotation angle monitoring method. Dashed lines and arrows indicate the calculation process.

2.2. Retroreflective Targets Deployment

The targets used in this study, as shown in Figure 3a, can reflect the incident light, thus improving the signal-to-noise ratio of the images and enhancing the contrast between the targets and the background light. The circular region of the vision target is made of glass bead retroreflective material with a reflective coating on the back surface, as shown in Figure 3b. Owing to the refractive index difference between glass and air, incident light is refracted and focused by the glass beads onto the back reflective layer. This light is then refracted and reflected along the incident direction, thus achieving retroreflection and contrast enhancement [33,34]. The retroreflective targets, when illuminated by LEDs, produce elliptical light spots in the images with well-defined edge contours, thus establishing robust visual features for target tracking. In addition, different from the conventional targets, the target in this section obviates the necessity for the electrical power supply that is required by conventional LED targets, thus significantly improving the operational convenience and monitoring sustainability.

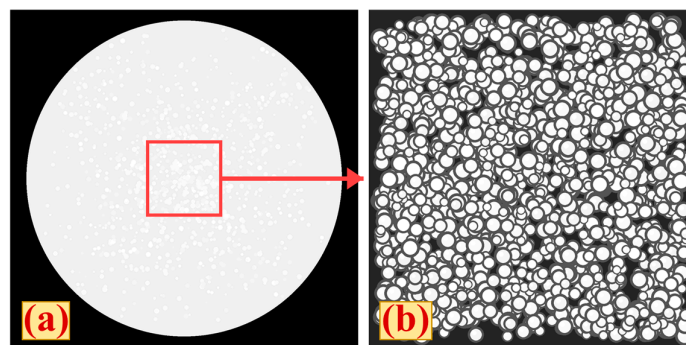


Figure 3. Schematic diagram of the target: (a) overall view; (b) microscopic view.

The arrangement scheme of the targets on the bridge bearing is shown in Figure 4. Specifically, two targets, marked as Target A and Target B, are attached to the surface of the upper plate, while the other two, marked as Target C and Target D, are similarly installed on the bottom plate. The centroid of each target is tracked using an ellipse fitting-driven target tracking method. Subsequently, the rotation angle of the bearing is determined by calculating the angular difference between two characteristic lines, i.e., line $\overline{AB}$ and line $\overline{CD}$, in which line $\overline{AB}$ is constructed by the centroids of Target A and Target B on the upper plate. Line $\overline{CD}$ is constructed by the centroids of the Target C and Target D on the bottom plate.

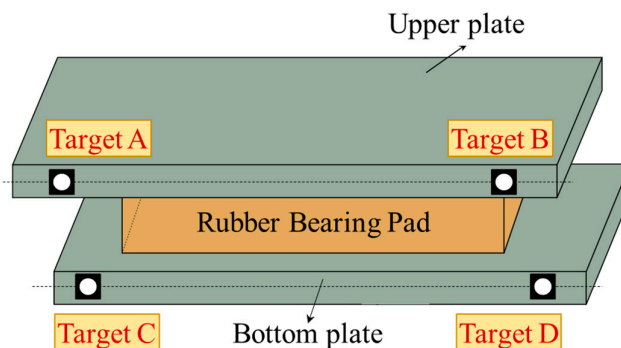


Figure 4. The arrangement scheme of the targets. Dashed lines indicate the centerlines of targets.

After target arrangement, the shooting camera is set in front of the target arranged plane. The optical axis of camera should be as perpendicular as possible to this plane to ensure that four targets are imaged, as shown in Figure 1.

2.3. Ellipse Fitting-Driven Target Tracking

The operation procedure of the target tracking method is as follows:

Step 1: We begin by determining the gray threshold T according to the ambient lighting conditions. Grayscale binarization is then performed to convert the original image into a binary image. The binarization is operated as follows [35]:

$$G(x,y) = \begin{cases} 0 & , f(x,y) \leq T \\ 255 & , f(x,y) > T \end{cases} \quad (1)$$

where $f(x, y)$ is the pixel intensity of the input image at pixel coordinates (x, y) ; T is the binarization threshold; and $G(x, y)$ is the binary image intensity at pixel (x, y) .

Step 2: The Canny algorithm [36], benefiting from its stability of performance and excellence of noise immunity, has been widely used to detect edges in different fields. Therefore, the Canny algorithm will be used here to performing edge detection on the binary image to extract the edge contours of each target.

Step 3: The elliptical curve is fitted on the detected edge pixels of each target [37]. The centroid pixel coordinates are obtained through least squares estimation according to the following equation:

$$ax^2 + bxy + cy^2 + dx + ey + 1 = 0 \quad (2)$$

$$x_c = \frac{be \cdot 2cd}{4ac - b^2} \quad (3)$$

$$y_c = \frac{bd - 2ae}{4ac - b^2} \quad (4)$$

where $a-e$ are the parameters of the ellipse equation obtained by fitting; and x_c and y_c are the horizontal and vertical pixel coordinates of the ellipse center, respectively.

2.4. Rotation Angle Calculation

After obtaining the center coordinates of the targets, the rotation angle calculation algorithm is utilized to analyze rotation angle θ of the bearing:

$$\theta = \arccos\left(\frac{|\overrightarrow{AB} \cdot \overrightarrow{CD}|}{|\overrightarrow{AB}| |\overrightarrow{CD}|}\right) \quad (5)$$

$$\overrightarrow{AB} = (x_b - x_a, y_b - y_a) \quad (6)$$

$$y_c = \frac{bd - 2ae}{4ac - b^2} \quad (7)$$

where x_a, x_b, x_c , and x_d are the horizontal pixel coordinates of Target A, Target B, Target C, and Target D, respectively; and y_a, y_b, y_c , and y_d are the vertical pixel coordinates of Target A, Target B, Target C, and Target D, respectively.

3. Numerical Analysis for Method Performance

In this section, the performance variation with the imaging conditions and the analysis of sensitivity were investigated for the proposed rotation angle computation method. These investigations are crucial because imaging conditions, such as camera pose and distance, vary considerably in practical measurement scenarios, directly affecting the accuracy of rotation angle estimation.

The remaining paper is organized as follows: The pinhole imaging-based analysis principle is described in Section 3.1. The numerical analysis environment and experimental conditions are given in Section 3.2. The investigation results of the measurement error of different test groups and measurement sensitivity are analyzed in Sections 3.3 and 3.4.

3.1. Analysis Principle

In order to investigate the performance of the proposed method, a series of controlled test groups was numerically simulated based on the pinhole imaging principle [38]. Bearing rotation can be expressed as target point coordinates in the world coordinate system; therefore, the goal of the pinhole imaging simulation is to calculate the corresponding pixel coordinates from the target point coordinates given in the world coordinate system. The numerical analysis procedure is as follows:

Step 1: Transforming target point coordinates (X_w, Y_w, Z_w) in the world coordinate system to obtain homogeneous vector, as shown in Equation (8):

$$P_w = [X_w, Y_w, Z_w, 1]^T \quad (8)$$

Step 2: Using camera extrinsic transformation to calculate target point coordinate P_c (X_c, Y_c, Z_c) in the camera coordinate system, as shown in Equation (9):

$$P_c = \begin{bmatrix} X_c \\ Y_c \\ Z_c \end{bmatrix} = [\mathbf{R} \mid \mathbf{t}] P_w \quad (9)$$

where $\mathbf{R} \in \text{SO}(3)$ (the Special Orthogonal Group of degree 3) and $\mathbf{t} \in \mathbb{R}^3$ (3-dimensional Euclidean space) are the camera extrinsic parameters that map a point from the world coordinate to the camera coordinate.

Step 3: Using camera intrinsic parameters to project target points into images to obtain pixel coordinates (x, y) , as shown in Equations (10) and (11):

$$p_c = \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} = \mathbf{K} P_c \quad (10)$$

$$\begin{cases} x = x_c / z_c \\ y = y_c / z_c \end{cases} \quad (11)$$

where p_c is the projected point in the camera coordinate system, and K is the camera intrinsic matrix.

3.2. Numerical Environment and Parameters

The numerical environment is as shown in Figure 5, where both the upper plate and the bottom have dimensions of $1500 \times 1000 \times 300$ mm, with a vertical centerline distance of 1000 mm between them. The horizontal spacing between targets is 1400 mm. The diameter of the circular region of each target is 80 mm. The shooting instrument, with a pixel size of $5.86 \mu\text{m}$ (H) $\times$ $5.86 \mu\text{m}$ (V) and resolution of 1920 pixels (H) $\times$ 1080 pixels (V), is

positioned 3170 mm in front of the bearing plane. The focal length of the lens used is 13 mm.

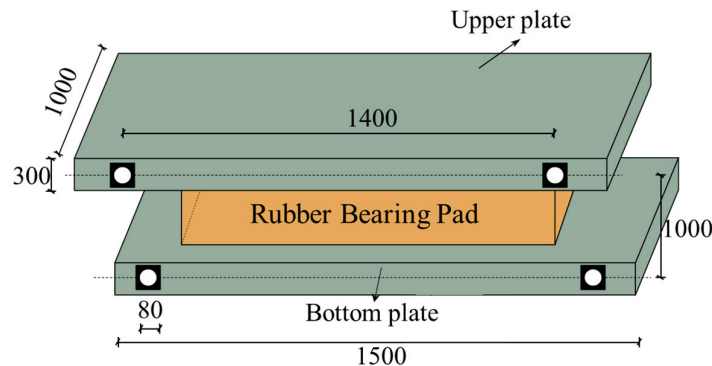


Figure 5. Dimensional schematic of the numerical validation. Dashed lines indicate the centerlines of targets (unit: mm).

Camera imaging angles, particularly yaw and pitch angles, are critical parameters that directly affect the geometric relationship between pixel coordinates and real-world dimensions, significantly influencing measurement accuracy. To investigate the influence of the camera imaging angle on the measurement results of the proposed method, variations in both camera yaw and pitch angles were introduced to the numerical analysis. Both the camera yaw angle and pitch angle were varied from -45° to 45° with an interval of 1° .

In the analysis, imaging distortion can be introduced by setting the tangential distortion coefficient k_0 and radial distortion coefficients k_1 to k_4 . To investigate the influence of imaging distortion on measurement results, 2000 sets of distortion states were varyingly configured, denoted as distortion ratio α ranging from -1 to 1 . For each state, the values of k_0 to k_4 are set to αd_0 , where $d_0 = [-0.2, -0.2, -2.5, -0.0025, -0.0025]$, denoting the distortion coefficient baseline. Taking the tangential distortion coefficient k_0 as an example, this coefficient was varied from -0.2 to 0.2 with an interval of 0.0002 .

To simulate camera motion interference, random vibration signals were applied to the six camera pose parameters, including yaw angle, pitch angle, roll angle, and translations along the x , y , and z directions.

Specifically, 11 groups of random angle noises were applied to the camera pose angles, i.e., yaw, pitch, and roll angles. For each group, 1000 random angle samples were introduced with standard deviations σ ranging from 0° to 1° at 0.1° intervals. Similarly, 11 groups of random translation noises were applied to the camera coordinates (x , y , z). For each group, 1000 random displacement samples were introduced with standard deviations σ ranging from 0 mm to 1 mm at 0.1 mm intervals.

The experimental conditions are set as shown in Table 1. For each state, multiple analyses were conducted with the ground truth angle uniformly varied from -0.1° to 0.1° in increments of 0.001° .

Table 1. Experimental conditions.

Test Group	Variable Range	Parameters						
		Object Distance (m)	Focal Length (mm)	Pitch Angle ($^\circ$)	Yaw Angle ($^\circ$)	Roll Angle ($^\circ$)	Distortion Ratio	Motion Effect
Pitch angle group	From 0° to 45° with an interval of 1° .	3.17	13	*	0	0	-	-
Yaw angle group	From 0° to 45° with an interval of 1° .	3.17	13	0	*	0	-	-
Camera distortion group	From $\alpha = -1$ to $\alpha = 1$, with an interval of 0.001 .	3.17	13	0	0	0	*	-

Motion interference group	From $\sigma = 0$ to $\sigma = 1$, with 0.1° intervals for rotations and 0.1 mm intervals for translations.	3.17	13	0	0	0	-	*
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Note: * marks the variable under investigation; - indicates no effect.

3.3. Investigation of Measurement Error

3.3.1. Evaluation Indicators

In this paper, three indicators, including absolute error $E_{i,a}$, relative error $E_{i,rel}$, and relative root mean square error [39] (denoted as $RMSE_{rel}$), were used to quantitatively evaluate the performance of the proposed method. These three indicators were calculated according to Equations (12)–(16):

$$E_{i,a} = |\theta_{i,true} - \theta_{i,test}| \quad (12)$$

$$E_{i,rel} = |\Delta\theta_{i,true} - \Delta\theta_{i,test}| \quad (13)$$

$$RMSE_{rel} = \sqrt{\frac{\sum_{i=1}^n (\Delta\theta_{i,true} - \Delta\theta_{i,test})^2}{n}} \quad (14)$$

$$\Delta\theta_{i,true} = |\theta_{i,true} - \theta_{0,true}| \quad (15)$$

$$\Delta\theta_{i,test} = |\theta_{i,test} - \theta_{0,test}| \quad (16)$$

where $E_{i,a}$ is the absolute error of the i -th state; $E_{i,rel}$ is the relative error of the i -th state; $RMSE_{rel}$ is the relative root mean square error; n is the number of states; $\Delta\theta_{i,true}$ is the ground truth of the relative rotation angle of the i -th state; $\Delta\theta_{i,test}$ is the measurement result of the relative rotation angle of the i -th state; $\theta_{i,true}$ is the ground truth of the bearing angle of the i -th state; $\theta_{i,test}$ is the measurement value of the bearing angle of the i -th state; $\Delta\theta_{0,true}$ is the ground truth of the reference state; and $\Delta\theta_{0,test}$ is the measurement value of the reference state.

3.3.2. Results Analysis

(1) Pitch angle analysis

Repeated processing was conducted on each of the aforementioned multiple analyses. Blender was used to generate the simulated image data for visualization [40,41]. Parts of the generated data for the pitch angle group are shown in Figure 6. As clearly observed in Figure 6, the pitch angle significantly affects the imaging projection, resulting in shape variations of the to-be-measured targets.

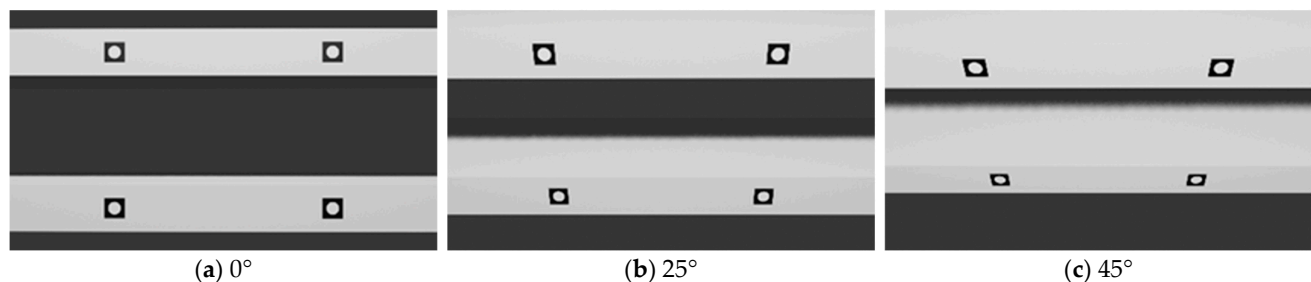


Figure 6. Parts of the generated image data for the pitch angle group.

Analysis results for the pitch angle group are presented in Figure 7. Figure 7a,b present the absolute and relative errors results, respectively, for pitch angles from 0° to 45° ,

with each state represented using boxplots of multiple measurements. Both error types exhibit a clear increasing trend with larger pitch angles, indicating significant impact on measurement performance. In Figure 7a, the absolute errors remain minimal ($<0.005^\circ$) at small pitch angles ($0\text{--}12^\circ$) but increase markedly beyond 20° , reaching approximately 0.035° at 45° . In Figure 7b, similarly, relative errors remain below 0.005 at small angles but rise sharply to approximately 0.05 at 45° . Figure 7c shows the RMSE increasing from near zero at 0° to approximately 0.015° at 45° , also confirming the dramatic decrease in measurement accuracy with larger pitch angles. These results demonstrate that the proposed method is sensitive to large pitch angles, with measurement accuracy decreasing significantly under such conditions.

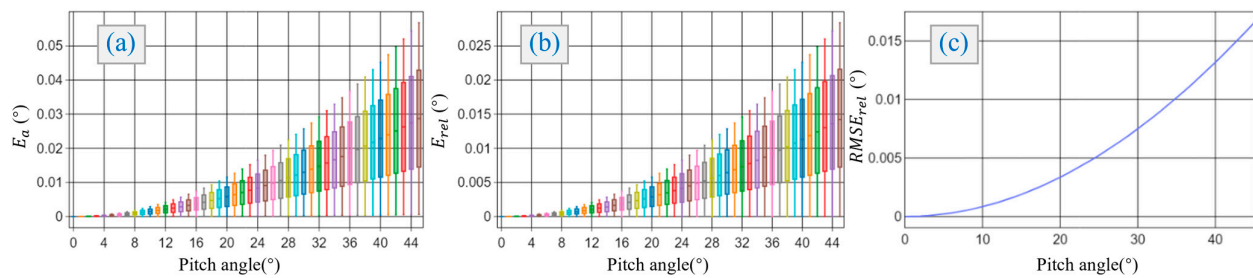


Figure 7. Results of the pitch angle group: (a) boxplot of E_a ; (b) boxplot of E_{rel} ; (c) $RMSE_{rel}$.

(2) Yaw angle analysis

Parts of the generated data for the yaw angle group are shown in Figure 8. Analysis results of the yaw angle group are presented in Figure 9. Figure 9a,b illustrate the absolute and relative errors results, respectively, for yaw angles ranging from 0° to 45° , with multiple measurements represented using a boxplot at each state.

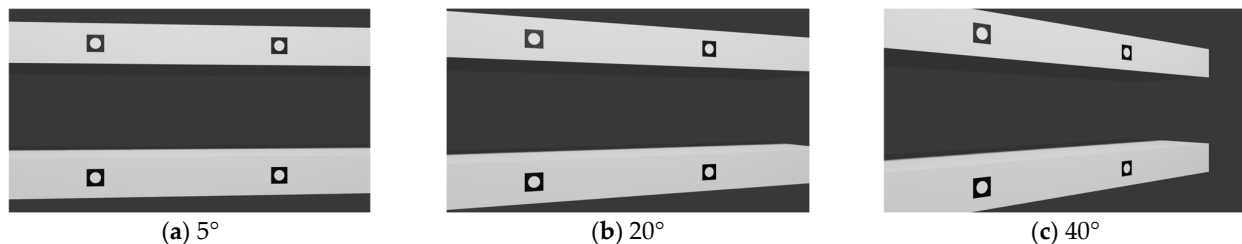


Figure 8. Parts of the generated image data for the yaw angle group.

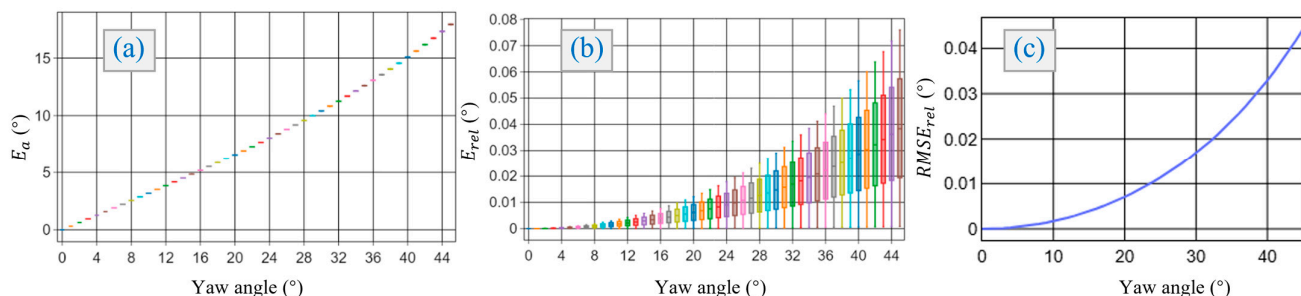


Figure 9. Results of the yaw angle group: (a) boxplot of E_a ; (b) boxplot of E_{rel} ; (c) $RMSE_{rel}$.

In Figure 9a, the absolute errors exhibit a progressively increasing trend with the yaw angle, rising from approximately 0° at small yaw angles to over 15° at a yaw angle of 45° . This trend reflects a worsening of geometric distortion caused by off-axis imaging as the

yaw angle grows, indicating that perspective projection errors become more pronounced, particularly at larger viewing angles.

In Figure 9b, relative errors show increasing variance with the yaw angle, indicating reduced stability under off-axis conditions. Measurement repeatability remains relatively stable within 0–25°, with errors concentrated below 0.03°. However, the error values exhibit a gradual increasing trend throughout the tested range, especially beyond 35°, where maximum errors reach 0.04–0.07°. In Figure 9c, the $RMSE_{rel}$ results also quantitatively confirm the increasing trend, showing a near-linear increase from approximately 0° at perpendicular viewing to 0.045° at a 45° yaw angle. These results demonstrate that while the proposed method maintains high accuracy within a moderate yaw angle range ($\leq 25^\circ$), perspective projection errors become pronounced at larger viewing angles. Therefore, strict angular constraints (preferably $\leq 30^\circ$) should be imposed during camera deployment to ensure measurement reliability in practical structural monitoring scenarios.

(3) Camera distortion analysis

Parts of the generated data for the camera distortion group are shown in Figure 10, exhibiting obvious distortion effects. Figure 11 illustrates the impact of the lens distortion ratio (α ranging from -1.0 to 1.0) on measurement accuracy. Figure 11a exhibits a distinctive V-shaped error variation, with minimum error (approximately 0°) at zero distortion and symmetric escalation reaching 0.06–0.08° at $|\alpha| = 1.0$. Figure 11b presents the detailed error distributions, showing increasing measurement uncertainty under severe distortions, with maximum individual errors reaching 0.0025° at extreme distortion levels. Figure 11c confirms a linear relationship between the RMSE and distortion ratio, escalating from 0 to $1.6 \times 10^{-4}^\circ$ at $|\alpha| = 1$. These results indicate that both barrel ($\alpha > 0$) and pincushion ($\alpha < 0$) distortions impose comparable adverse effects, demonstrating rapid degradation of measurement performance with increasing distortion. Therefore, maintaining low optical distortion is recommended to ensure increase accuracy.

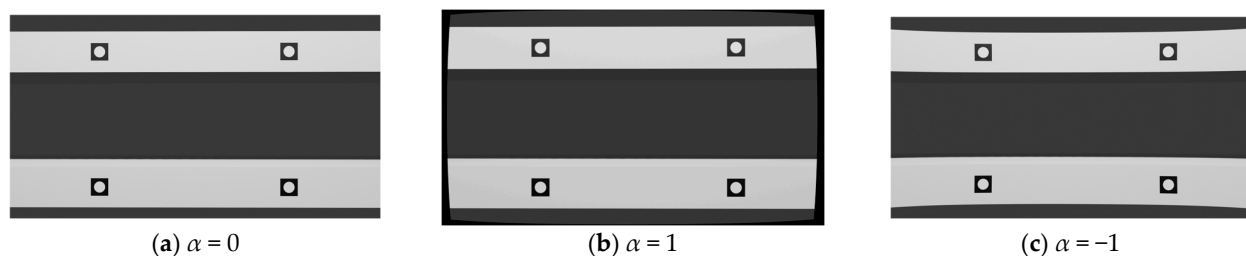


Figure 10. Parts of the generated image data for the camera distortion group.

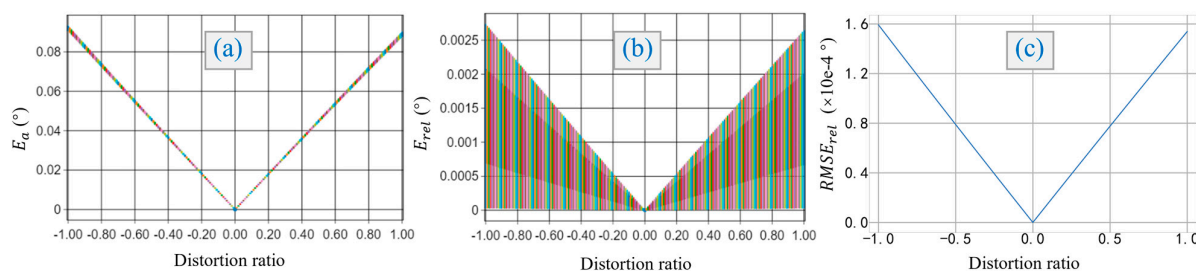


Figure 11. Results of the camera distortion group: (a) boxplot of E_a ; (b) boxplot of E_{rel} ; (c) $RMSE_{rel}$.

(4) Motion interference analysis

Figure 12 illustrates the $RMSE_{rel}$ result of the proposed method induced by motion interference under varying camera pose parameters (σ ranging from 0.0 to 1.0). In Figure

12a, the $RMSE_{rel}$ increases gradually with pitch angle interferences, reaching approximately 0.0006° at $\sigma = 1.0^\circ$, indicating that pitch angle errors have a moderate impact on measurement accuracy. Figure 12b demonstrates that yaw angle interferences induce a larger $RMSE_{rel}$ increase to approximately 0.30° at $\sigma = 1.0^\circ$, showing greater impact on measurement accuracy compared to the pitch angle. In contrast, Figure 12c reveals that roll angle interferences have negligible impact, with $RMSE_{rel}$ remaining nearly constant at approximately $6.8 \times 10^{-7^\circ}$ across different σ values. Figure 12d shows that translational interferences along the x-axis have minimal effect on accuracy, with the $RMSE_{rel}$ maintaining at approximately $6.77 \times 10^{-7^\circ}$ throughout the entire range (0–1 mm). Similarly, Figure 12e indicates that y-axis translations exhibit the same exceptional stability, with the $RMSE_{rel}$ remaining constant at approximately $6.77 \times 10^{-7^\circ}$. Figure 12f confirms that z-axis translations also demonstrate outstanding immunity to interferences, maintaining an $RMSE_{rel}$ of approximately $6.77 \times 10^{-7^\circ}$ throughout the tested range.

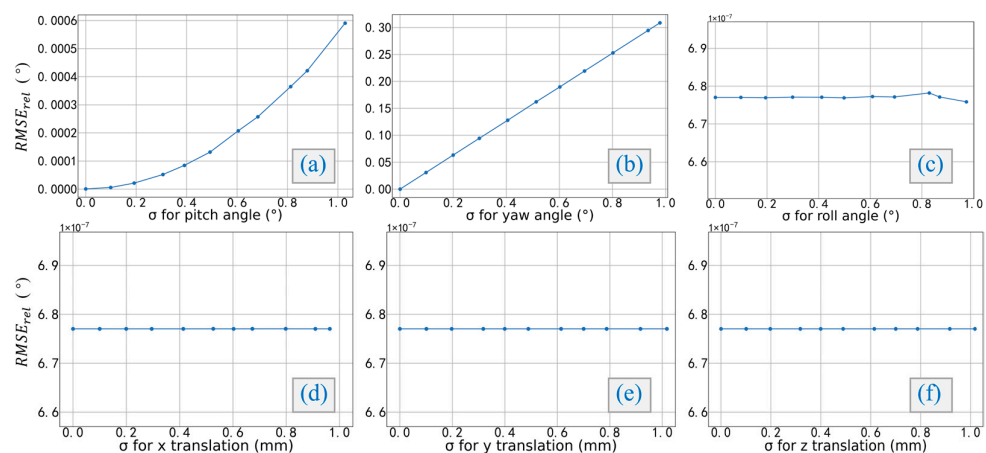


Figure 12. $RMSE_{rel}$ of the motion interference group: (a) pitch angle; (b) yaw angle; (c) roll angle; (d) x translation; (e) y translation; (f) z translation.

Comparison across the six interference parameters reveals distinct performance differences. The yaw angle functions as the dominant factor with the highest error (0.30° at $\sigma = 1^\circ$), followed by the pitch angle with moderate influence (0.0006°). The roll angle and all three translational factors demonstrate nearly identical impacts, with $RMSE_{rel} \approx (6.77\text{--}6.8) \times 10^{-7^\circ}$, indicating that the proposed method is fundamentally immune to the interferences of these four degrees of freedom. In summary, regarding the impact on measurement accuracy of the proposed method, the pitch angle and yaw angle can be regarded as critical parameters, while the other four parameters (roll angle and translations) can be regarded as non-critical parameters. This provides practical guidance for camera installation: strict control is required for pitch and yaw angles, whereas roll stabilization and translational constraints can be relatively relaxed. This difference stems from the fundamental imaging principle: pitch and yaw angles directly affect the image-to-world coordinate transformation, whereas the roll angle and translations do not alter the relative angular relationships between features.

3.4. Investigation of Measurement Sensitivity

3.4.1. Evaluation Indicators

In the bearing rotation scenario, the measurement sensitivity is mainly characterized by the quantitative mapping between a unit rotation angle and the resulting vertical pixel displacement. However, this mapping varies with the actual magnitude of the rotation. In

this section, the sensitivity of the proposed method is calculated by the least squares regression on the slope relationship between group truth and the measured pixel results [42]. The calculation equation of the sensitivity S is as follows:

$$S = \frac{n \sum_{i=1}^n d_i^2 - \left(\sum_{i=1}^n d_i \right)^2}{n \sum_{i=1}^n (d_i \theta_{i,true}) - \sum_{i=1}^n d_i \sum_{i=1}^n \theta_{i,true}} \quad (17)$$

where S is the sensitivity; n is the number of states; $\theta_{i,true}$ is the ground truth of the bearing angle of the i -th state; and d_i is the vertical displacement measurement value of the bearing of the i -th state.

3.4.2. Sensitivity Analysis

As illustrated in the above analysis, the camera pitch angle and yaw angle are two key factors influencing the measurement performance of the proposed method. In addition, the target baseline (horizontal distance between targets) and object distance [43] also significantly affect the measurement performance. Therefore, this section investigates the sensitivity of the method to four parameters: pitch angle, yaw angle, target baseline, and object distance. Pitch angle and yaw angle configurations remain consistent with the settings in Section 3.1. For the baseline variation group, the horizontal distance between targets was uniformly varied from 0.2 m to 1.2 m in 0.01 m increments. For the sensitivity analysis of object distance effects, the object distance ranged from 2.4 m to 7.2 m in 0.02 m increments. For each state in the above four groups, multiple analyses were conducted with the support angle uniformly varied from -0.1° to 0.1° in 0.001° increments.

Representative generated images for the baseline and distance variation groups are shown in Figure 13. As can be seen in Figure 13a–c, the images exhibit obvious imaging distinction in the configuration of the target baseline. Similarly, Figure 13d–f demonstrate clear imaging distinctions under different object distance settings, where the apparent target size decreases as the object distance increases.



Figure 13. Parts of the generated image data for the yaw angle group: (a) 0.2 m baseline; (b) 0.6 m baseline; (c) 1.2 m baseline; (d) 2.4 m object distance; (e) 4.8 m object distance; (f) 7.2 m object distance.

Sensitivity analysis results are shown in Figure 14, providing critical insights into the robustness of the proposed method under varying system configurations. As shown in

Figure 14a, both the pitch and yaw angles exhibit negative influence on measurement sensitivity, with the yaw angle demonstrating a more pronounced declining trend. The sensitivity decreases from approximately 4.5 pixels/degree at 0° to 4.4 pixels/degree at 45° for the yaw angle, while the pitch angle shows a more gradual reduction from 4.6 to 2 pixels/degree across the same range. This indicates that the pitch angle imposes stricter geometric constraints than the yaw angle, highlighting the need to prioritize its control during practical deployment to maintain measurement consistency.

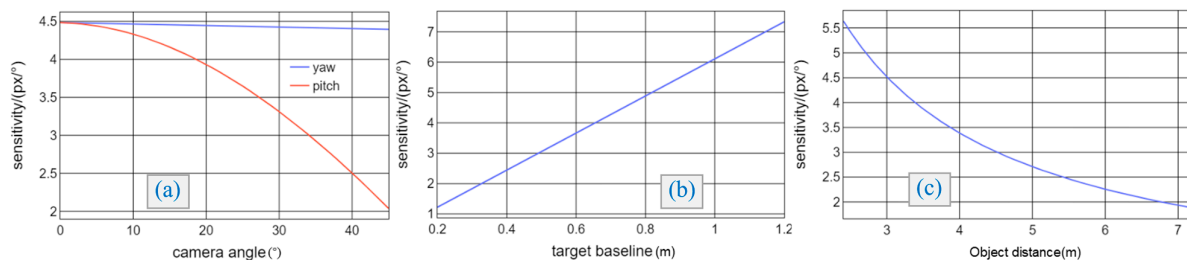


Figure 14. Sensitivity analysis results: (a) pitch and yaw angles; (b) target baseline; (c) object distance.

Figure 14b reveals a strong linear relationship between the target baseline and sensitivity, showing a rapid increase from approximately 1.2 pixels/degree at 0.2 m to 7.2 pixels/degree at a 1.2 m baseline distance. This linear trend confirms the advantage of a larger baseline for enhancing sensitivity, though real-world installation limits must be considered to ensure operational feasibility.

In Figure 14c, the object distance factor exhibits a strong negative impact on sensitivity, decreasing from 5.6 pixels/° at 2 m to 2.1 pixels/° at 7 m. This relationship stems from the diminishing resolution with increasing distance. This result underscores a fundamental trade-off in vision-based measurement methods: while greater object distances provide practical advantages (reduced installation complexity, broader field of view, and so on), it inherently compromises measurement sensitivity.

3.5. Summary

This section comprehensively investigated the performance characteristics of the proposed rotation angle measurement method through systematic numerical analyses based on pinhole imaging simulations. Four critical aspects were examined: imaging angle effects (pitch and yaw), lens distortion, motion interference, and measurement sensitivity. The findings are concluded as follows:

- (1) Regarding imaging angle influence, the pitch axis behaves benignly: as the pitch angle increases from 0° to 45° , the relative RMSE grows almost linearly from the noise floor to 0.015° , a level that remains acceptable for most structural monitoring tasks. In contrast, the yaw axis exhibits a markedly steeper error gradient, producing a three-fold larger RMSE of approximately 0.045° at 45° , thereby establishing yaw as the dominant alignment constraint during field deployment. Consequently, both angles should be minimized during camera deployment, with cameras positioned to face targets perpendicularly to preserve accuracy.
- (2) Lens distortion introduces a deterministic, linear error: the relative RMSE increases smoothly from 0° to $1.6 \times 10^{-4}^\circ$ as radial distortion coefficient $|\alpha|$ rises from 0 to 1.0. Because this increment is two orders of magnitude smaller than errors induced by yaw misalignment, distortion can be safely neglected in routine field applications without explicit calibration.

- (3) Motion interference analysis reveals that a 1° perturbation in yaw generates an RMSE of 0.30° , an order of magnitude larger than the 0.0006° induced by the same pitch disturbance. Roll and all three translational degrees of freedom, however, contribute negligible errors on the order of $6.8 \times 10^{-7^\circ}$, which implies that only pitch and yaw require mechanical stabilization, whereas roll and translational tolerances may be relaxed without compromising accuracy.
- (4) Measurement sensitivity decreases monotonically with increasing pitch angle, falling sharply from 4.6 to 2.0 pixels/ $^\circ$ across the $0\text{--}45^\circ$ range, thereby confirming pitch as the most critical parameter for sensitivity. Conversely, sensitivity scales linearly with target baseline, rising six-fold over the tested interval, so the largest feasible baseline should always be selected. Object distance exerts a uniform negative effect, so the shortest practical stand-off distance is preferred to preserve sensitivity.

4. Comparison with Existing Advanced Method

Su et al. [24] developed a rotation angle measurement approach for bridge bearings based on the Planar Perspective-n-Point (PnP) method, which determines the relative displacement and rotation between the camera and the target coordinate system by matching 3D coordinates of feature points with the corresponding 2D image projections. To comprehensively evaluate the performance and advantages of the proposed dimension measurement solution, this section compares it with existing advanced methods reported in the literature [24], using the analysis based on the pinhole imaging principle.

In practical applications of bridge engineering, due to the adverse influence brought from real-world engineering conditions such as varying illumination and environmental effect (such as rain, fog, dust, and temperature variation), target tracking cannot be perfectly accurate, inevitably introducing pixel localization errors. Therefore, to evaluate the robustness and comparative performance of the two methods, this section systematically analyzes the influence of the target tracking error of both the proposed method and the PnP-based approach. Gaussian random noise was added to the pixel coordinates of each tracking result to introduce the target tracking errors. The standard deviation (σ) of the additive noise was uniformly increased from 0 to 0.1 pixels in steps of 0.01 pixels, with 1000 independent tests conducted at each noise level.

As demonstrated in Figures 15 and 16, the proposed method exhibits significantly greater resilience to target tracking errors compared to the PnP-based approach. Under ideal conditions with zero tracking error, the proposed method achieves nearly negligible measurement errors, with the median and quartile values concentrated near zero. Even at a tracking error of 0.1 pixels, it maintains a maximum error of only about 0.03° , indicating a stable and linear error propagation behavior. In contrast, as can be seen in Figures 15b and 16b, the PnP-based method shows notably higher sensitivity, with baseline errors around $0.1\text{--}0.2^\circ$ under perfect tracking and median errors rising to $1.0\text{--}1.2^\circ$ at 0.1-pixels tracking error. These values represent an error magnitude approximately 30–40 times larger than that of the proposed method accompanied by pronounced variability, which reflects a nonlinear and unstable error propagation pattern.

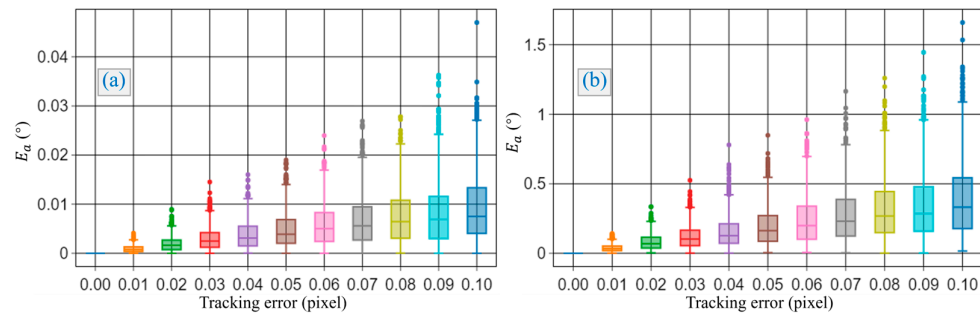


Figure 15. Boxplot of E_a : (a) the proposed method; (b) the PnP method.

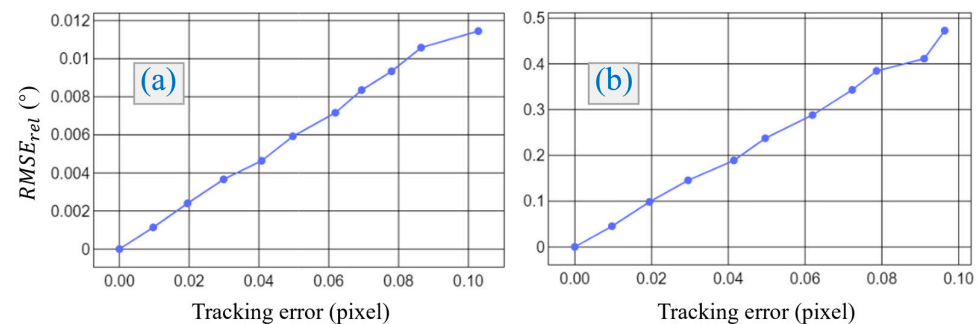


Figure 16. $RMSE_{rel}$ of the tracking error analysis: (a) the proposed method; (b) the PnP method.

The above fundamental distinction stems from the different computational principles of the two methods. The PnP-based method depends on precise 3D–2D point correspondences and is highly susceptible to pixel-level uncertainties due to its nonlinear optimization process. In contrast, the proposed method employs direct 2D angular computation, providing more predictable and acceptable error characteristics. Consequently, the proposed method sustains high measurement accuracy even under significant tracking uncertainties, making it well suited for practical bridge monitoring environments where tracking performance cannot be guaranteed, while the PnP method demands near-perfect tracking accuracy below 0.1 pixels to attain similar precision. In summary, the above comparison confirms the superior robustness of the proposed method to tracking errors compared to the conventional PnP-based method.

5. Field Application on the Real Bridge

In order to validate the effectiveness and applicability of the proposed method, especially under practical application conditions, an outdoor monitoring application was conducted on a real bridge in this section. The field application was conducted on a steel box girder bridge located in the Xiaojunshan–Zhuankou section of Wuhan Metro Line 16 on 20 March from 20:00 to 22:00. A total of 23 in-service train crossings were recorded during the monitoring period.

This bridge is an 80 m + 80 m continuous beam bridge, and the bearing under test sits atop the intermediate pier, as shown in Figure 17. During monitoring, an industrial camera was installed on the bridge, positioned at a distance of approximately 1.5 m from the targets with a downward pitch angle of -1.5° . The resolution and focal length of the used shooting instrument are 1440 pixel (H) $\times$ 1080 pixel (V) and 6 mm, respectively. Six targets in total were attached to the bridge bearings, of which only four targets, named #1–#4 in Figure 17, were used for calculation. Each to-be-used target consisted of a black square background with a length of 13 cm and a white circular marker with a diameter of 8 cm. Infrared LED lights were installed at the site to provide supplementary illumination. Two

displacement gauges and an inclinometer were installed near the targets to provide a reference rotation angle for validating the vision-based results.

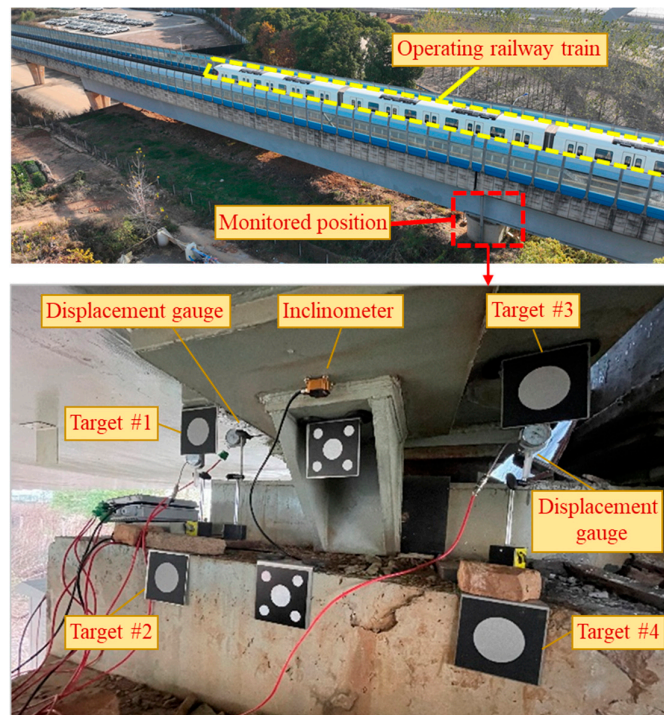


Figure 17. Experimental setup.

Two displacement gauges and an inclinometer were installed on the bridge to provide two independent sources of rotation angle reference. The first reference was obtained by calculating the rotation angle from the displacement difference between the two gauges, while the second reference was provided directly by the inclinometer measurements. This dual-source reference ensured robust validation of the proposed vision-based method. The technical specifications of the devices used in this section are listed in Table 2. As shown in Figure 18, two displacement gauges were installed as close as possible to the targets to ensure that the reference measurements corresponded to the same locations as the vision-based measurements. The horizontal distance between them was 995 mm.

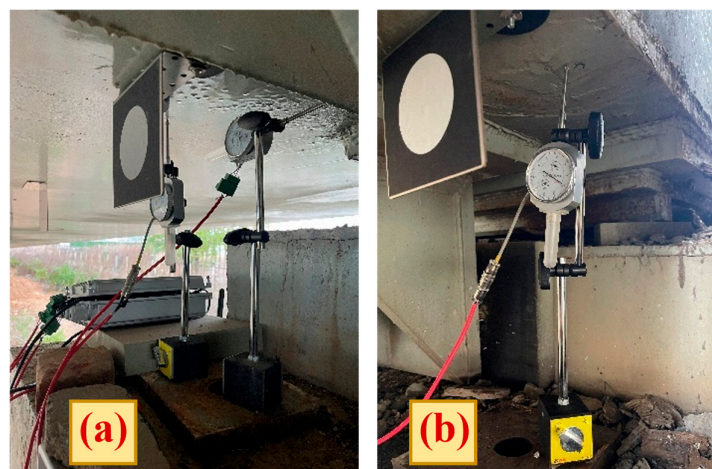
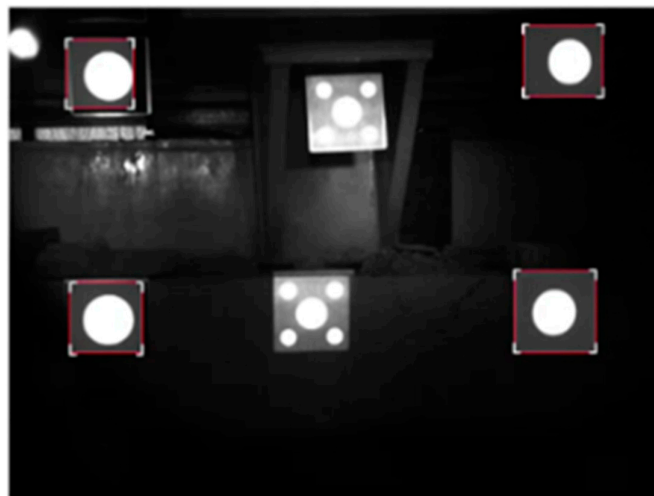


Figure 18. Displacement gauge installation configurations: (a) at the position of Target #1; (b) at the position of Target #2.

Table 2. Technical specification for the devices to be used.

Device	Model	Technical Characteristics
Displacement gauge	WBD-50B	Measurement range: 0–50 mm Accuracy: $\leq \pm 0.1$ mm Resolution: 0.01 mm
Dual-axis inclinometer	SCI-RQJ900	Measurement range: $\pm 90^\circ$ Accuracy: 0.001° Resolution: 0.001°

The representative captured image is shown in Figure 19. Throughout the monitoring period, 23 train-crossing events were recorded, providing multiple loading cycles for validation analysis. The proposed method was employed to process the image data and calculate the bearing rotation angle. Figure 20 provides a comprehensive comparison of the rotation angle measurements obtained from three independent sources: the displacement-based calculation (derived from two displacement gauges), the inclinometer measurement, and the proposed vision-based method. Magnified views of the time segments are presented in Figure 21a,b, respectively, to facilitate a detailed comparison of the measurement results. As shown in Figure 20, a total of 23 peaks were observed in the rotation angle time series, consistent with the number of recorded train-crossing events. Each peak corresponds to a train passage event, indicating that all three measurement methods accurately captured the bearing rotation dynamics induced by train loading. Regarding the peak values, all three methods captured peak rotation angles within the 0.012 – 0.02° range. The vision-based method and displacement-based calculation produced peak values of approximately 0.02° , while the inclinometer recorded peaks around 0.013° . The rotation angle curves from the vision-based and displacement-based measurements exhibit relatively smooth profiles, whereas the inclinometer measurements display pronounced rough fluctuations, indicating lower resolution compared to the other two measurements.

**Figure 19.** Part of the recorded image data. Red squares denote the analyzed targets.

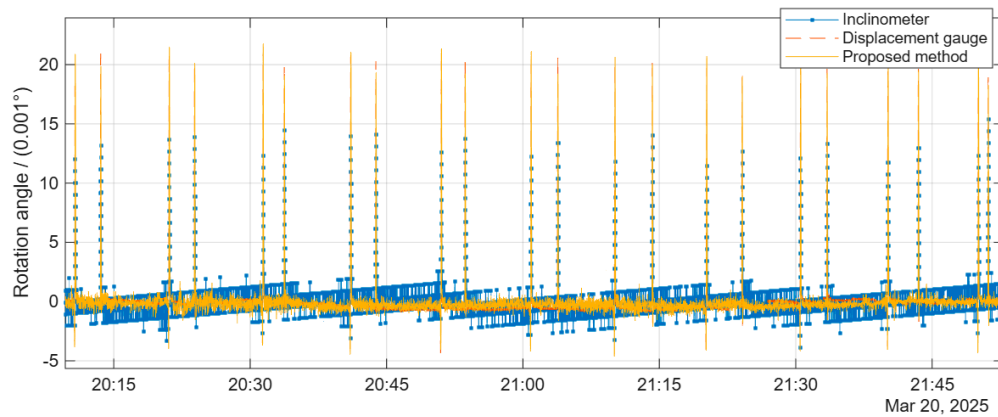


Figure 20. Comparison of the rotation angle measurement results.

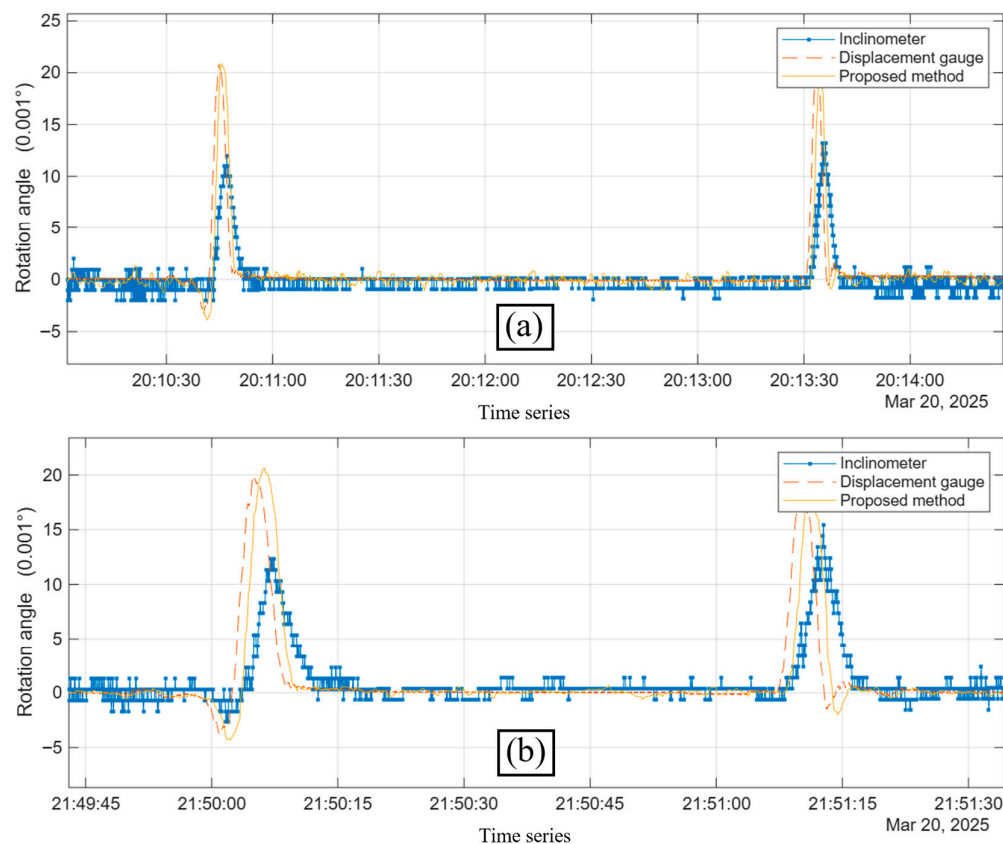


Figure 21. Magnified views of Figure 20 with the measurement time at: (a) 20:10:00~20:14:30; (b) 21:49:42~21:51:34.

As can be seen in Figure 20, all three measurements demonstrate highly consistent peak occurrence times throughout the monitoring, confirming their ability to accurately track the bearing rotation dynamics. However, in Figure 21, minor time offsets (typically within ± 0.5 – 1.0 s) are observed between peak locations. These slight temporal shifts can be attributed to imperfect time synchronization among the three measurements, as each measurement operated with its own independent data acquisition timing.

To further quantify the measurement accuracy, statistical analysis of the rotation angle measurement errors was performed for both the proposed method and the inclinometer, with the displacement gauge calculations as the reference. The error statistics for all 23 train-crossing events are summarized in Table 3. Comparison results of the statistical

analysis index are shown in Table 4. The mean error (ME) is -0.0001° , the mean absolute error (MAE) is 0.0007° , the standard deviation (SD) is 0.0008° , and the root mean square error (RMSE) is 0.0008° . In comparison, the inclinometer exhibits larger measurement error with $ME = -0.0070^\circ$, $MAE = 0.0070^\circ$, $SD = 0.0012^\circ$, and $RMSE = 0.0071^\circ$ (approximately 9.15 times that of the proposed method). The results reveal excellent agreement between the proposed method and the displacement gauge reference measurements. All statistical indicators for the inclinometer exhibit substantially larger errors than those of the proposed vision-based method, confirming that the proposed vision-based method achieves measurement accuracy superior to the inclinometer and comparable to high-precision displacement-based calculations. Furthermore, the larger inclinometer errors can be attributed to its measurement baseline. The inclinometer measures the rotation angle with gravitational direction as a baseline, rather than the bearing bottom plate. As a result, train-induced deformations of the bridge bottom plate are not captured in its measurements, thus leading to larger errors compared to other two methods. Finally, all these results validate the practical viability of the proposed method for field deployment, demonstrating its effectiveness and feasibility as a reliable, non-contact monitoring solution for operational bridge infrastructure.

Table 3. Comparison for calculation results of the rotation angle.

Number	Displacement Gauge	Proposed Method		Inclinometer	
	Peak Angle ($^\circ$)	Peak Angle ($^\circ$)	Error ($^\circ$)	Peak Angle ($^\circ$)	Error ($^\circ$)
#1	0.0200	0.0194	-0.0006	0.015	-0.0054
#2	0.0208	0.0209	0.0001	0.012	-0.0088
#3	0.0209	0.0199	-0.0011	0.013	-0.0077
#4	0.0207	0.0215	0.0008	0.014	-0.0070
#5	0.0203	0.0201	-0.0002	0.014	-0.0064
#6	0.0208	0.0217	0.0009	0.012	-0.0085
#7	0.0199	0.0190	-0.0008	0.014	-0.0054
#8	0.0208	0.0210	0.0003	0.014	-0.0068
#9	0.0203	0.0193	-0.0010	0.014	-0.0062
#10	0.0203	0.0213	0.0010	0.013	-0.0077
#11	0.0205	0.0192	-0.0013	0.014	-0.0068
#12	0.0200	0.0211	0.0011	0.012	-0.0078
#13	0.0206	0.0192	-0.0014	0.013	-0.0072
#14	0.0199	0.0207	0.0008	0.012	-0.0081
#15	0.0203	0.0200	-0.0003	0.014	-0.0063
#16	0.0197	0.0207	0.0010	0.011	-0.0083
#17	0.0194	0.0190	-0.0004	0.013	-0.0067
#18	0.0198	0.0199	0.0001	0.012	-0.0077
#19	0.0196	0.0193	-0.0004	0.013	-0.0064
#20	0.0199	0.0199	0.0000	0.012	-0.0082
#21	0.0196	0.0195	-0.0001	0.013	-0.0067
#22	0.0198	0.0206	0.0008	0.012	-0.0075
#23	0.0189	0.0183	-0.0007	0.015	-0.0035

Table 4. Comparison results of statistical analysis index.

Method	ME ($^\circ$)	MAE ($^\circ$)	SD ($^\circ$)	RMSE ($^\circ$)
Proposed method	-0.0001	0.0007	0.0008	0.0008
Inclinometer	-0.0070	0.0070	0.0012	0.0071

6. Discussion

- (1) The proposed method assumes that the bearing rotates as a rigid planar body while its tolerance is clear: in-plane sliding or eccentric rotation leaves the target chord angle unchanged; out-of-plane sliding of millimeters adds $<10^{-7^\circ}$ error, as can be seen in Figure 12f. Local deformation violates assumption severely and demands a collocated inclinometer to complement the proposed vision technique. Hence, the method is valid for bearings dominated by in-plane rotation. Whenever local deformation occurs, the shared target plane introduces uncontrollable tilt errors, and a contact inclinometer must be added within the deformed zone to cover this mechanism.
- (2) By capturing the bearing surface nearly perpendicularly, the planar pixel displacements of control points are used to estimate the rotation angle; consequently, the camera optical axis should be as perpendicular to the bearing plane as possible. However, only rotations about the axis normal to the image plane can be detected; the other directions' rotations remain insensitive or undetectable. Future work will pursue high-precision monitoring of multi-dimensional rotations.
- (3) As previously noted, when real-world image noise is present, planar PnP suffers from coupled pose degrees of freedom and insufficient depth constraints, often yielding large angular errors. For in-plane rotation estimation, it is clearly outperformed by the proposed method. In future work, a dedicated 3-D vision target may be developed to push accuracy even higher.
- (4) While this study focuses on achieving high-accuracy, robust bearing rotation measurements, subsequent research will leverage these data for condition assessment. By compiling rotation, strain, deflection, acceleration, and environmental datasets from the case study bridge and incorporating them into an explainable machine learning-enhanced digital twin [44–47] with continuously updated finite element models, sub-millidegree angular signatures can be transformed into physics-informed system-level degradation patterns and mitigation measures.
- (5) The proposed method relies on artificially designed targets and geometry-based image processing, a pathway that offers high controllability and has therefore been widely adopted for both short- and long-term structural deformation monitoring [11,48]. It is technically feasible to replace artificial targets with semantic segmentation or object detection networks [49,50] that track natural bridge components directly. This “target-free” route eliminates on-site installation but demands large, high-quality annotated datasets to achieve sub-pixel accuracy. How to secure millimeter-level precision under varying illuminations, viewpoints, and surface textures while keeping the annotation cost manageable is still an open question.
- (6) For standardized field deployment, the baseline B between retroreflective targets is determined first and taken as close as possible to the usable length of the bearing plate depending on field situation, which is the largest practically rigid region available. With B thus set, the object distance D is chosen last by the pinhole relation, as shown in Equation (18), where f is the selected focal length, W is the camera sensor width in pixels, and p is the pixel size; this yields the minimum object distance that keeps all four targets within the image. If structural clearance is tight, a longer focal lens or higher-resolution camera is substituted while still using Equation (18).

$$D = \frac{Bf}{Wp} \quad (18)$$

7. Conclusions

This study has established a robust computer vision-based methodology for monitoring bridge bearing rotation angles, specifically designed to overcome the limitations of existing methods under time-varying operational conditions. The proposed approach integrates custom-configured retroreflective targets, a reliable target tracking algorithm, and a straightforward yet effective rotation angle calculation model. Through comprehensive validation, the core contributions and implications of this research can be summarized as follows:

(1) The methodology demonstrates a principled design that balances accuracy, robustness, and practicality. The use of passive retroreflective targets ensures high image contrast and operational sustainability, while the direct 2D angular computation from target lines provides inherent invariance to camera translations and in-plane rotations.

(2) Extensive numerical analyses have quantitatively validated the method's performance boundaries, confirming its high accuracy within a practical range of camera viewing angles and its definable sensitivity to key parameters like target baseline and object distance, thereby providing clear guidelines for optimal field deployment.

(3) A comparative analysis against a contemporary PnP-based method underscores a fundamental advantage: superior resilience to target tracking errors. The proposed method maintained an accuracy below 0.03° even with a substantial 0.1-pixel tracking error, a scenario where the PnP approach suffered from significantly amplified and unstable errors.

(4) The successful field application on an in-service bridge confirms its practical viability. The vision-based measurements achieved exceptional agreement with high-precision displacement gauge references, with an RMSE of 0.0008° and an MAE of 0.0007° , outperforming conventional inclinometer measurements by a factor of approximately 9.15.

In conclusion, this work not only presents a validated technical solution for a critical monitoring task but also highlights the significant potential of robust, purpose-built vision-based systems for long-term structural health monitoring. The method offers a non-contact, accurate, and practical alternative for assessing bridge bearing behavior under operational loads.

Future research will focus on developing self-calibrating systems that automatically compensate for camera pose variations to reduce installation constraints and maintenance requirements. Additionally, the applicability of the proposed approach to other structural monitoring scenarios, such as building tilt detection and large-span structure deformation monitoring, to broaden its impact beyond bridge engineering.

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