

DUAL-Calib: Joint LiDAR-Dual-Camera Extrinsic Calibration with Automatic Target Corner Detection

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Abstract: This paper presents the DUAL-Calib calibration framework, which enables joint constrained extrinsic calibration of a single LiDAR and two cameras. As an optimized extension of FAST-Calib for multi-camera scenarios, DUAL-Calib establishes a unified optimization framework with inter-camera rigid geometric constraints to enhance calibration consistency and solve the cumulative error problem caused by independent calibration. Furthermore, this paper proposes an automatic corner detection algorithm based on ArUco marker triangulation, which avoids manual on-site measurement of the target's physical dimensions and enables automated field calibration. It can directly reconstruct the target coordinate system from the detected markers, realizing semi-automated calibration with reduced manual measurement. Experimental verification was performed on a wheel loader platform equipped with the Lingmou S1 perception module (integrating a Livox Mid360 LiDAR and two wide-angle fisheye cameras), with the calibration target placed within the overlapping field of view of the sensors at a distance of 1.5–4.5 m. The results demonstrate that the point-to-point registration error of DUAL-Calib on both camera channels is less than 5.0 mm under normal conditions and remains below 5.8 mm even under vibration interference. Compared with FAST-Calib's independent single-camera calibration method, DUAL-Calib reduces the calibration errors of LiDAR-Camera A and LiDAR-Camera B by 37.5% and 36.0% respectively with significantly lower variance, and the proposed automatic corner extraction method achieves sub-centimeter accuracy compared with manual measurement, effectively bridging the practicality gap between laboratory calibration and on-site deployment of construction machinery vehicles.

Key Words: LiDAR-Dual-Camera Calibration, Extrinsic Calibration, Construction Machinery, Multi-Sensor Fusion

1 Introduction

The extrinsic calibration between LiDAR and cameras is a fundamental prerequisite for multi-sensor fusion in autonomous driving and robotics, and is widely applied in tasks such as mapping[1,2], object detection[3,4]. Although significant progress has been achieved in the calibration of a single LiDAR and a single camera[5–7], modern robotic systems are increasingly adopting multi-camera configurations to expand the perception range. Engineering vehicles, agricultural machinery, and autonomous trucks typically employ two or more cameras to eliminate blind spots and improve operational safety[8].

However, calibrating each pair of sensors independently in such systems introduces cumulative errors and fails to leverage the inherent geometric constraints between cameras. Existing target-based calibration methods, such as FAST-Calib[9], achieve millimeter-level calibration accuracy by detecting circular holes on custom three-dimensional targets. These methods rely on pre-measured physical dimensions of the target and require manual input of geometric parameters, including hole positions and board sizes. In factory environments, standardized processes can ensure measurement accuracy; however, in on-site deployments (e.g., construction sites), precision measurement tools cannot be used for rapid re-calibration. The inability to automatically estimate target dimensions significantly limits the operational flexibility of the system.

In addition, independent calibration of multiple cameras neglects the rigid transformation constraints between them. When cameras are mounted on a rigid chassis, their relative poses remain unchanged, providing valuable geometric redundancy information. Existing methods[10, 11] treat multi-

camera calibration as a serial single-camera problem, which may result in inconsistent results that violate physical rigid constraints.

To address the aforementioned issues, this paper proposes DUAL-Calib, which extends FAST-Calib to a dual-camera scenario and enables automatic target parameter estimation. The main contributions are threefold:

- 1) A unified dual-camera constrained calibration framework that incorporates inter-camera rigid constraints to achieve consistent LiDAR-dual-camera extrinsic estimation under a known high-precision baseline.
- 2) Automatic target corner reconstruction without manual measurement using ArUco triangulation and plane fitting, which improves flexibility for field deployment.
- 3) A rapid on-site calibration pipeline for construction machinery with $O(N)$ time complexity and execution time below 1 second, robust to vibration and lighting variations.

2 RELATED WORK

2.1 Multi-camera-LiDAR Calibration

Most existing LiDAR-camera calibration methods focus on single-camera configurations. Target-based methods [5, 6, 9] establish 3D-2D correspondences using dedicated calibration boards, while target-free methods [7] leverage environmental features such as edges and planes. However, research on extending these methods to multi-camera scenarios remains limited. Geiger et al. [12] proposed a calibration method for multi-camera systems, but it requires overlapping camera fields of view and separate processing for LiDAR calibration. Li et al. [13] performed sequential calibration of multiple cameras and LiDAR without imposing inter-camera consistency constraints. In contrast, the method proposed in this paper explicitly models the rigid constraints between

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cameras within a unified optimization framework.

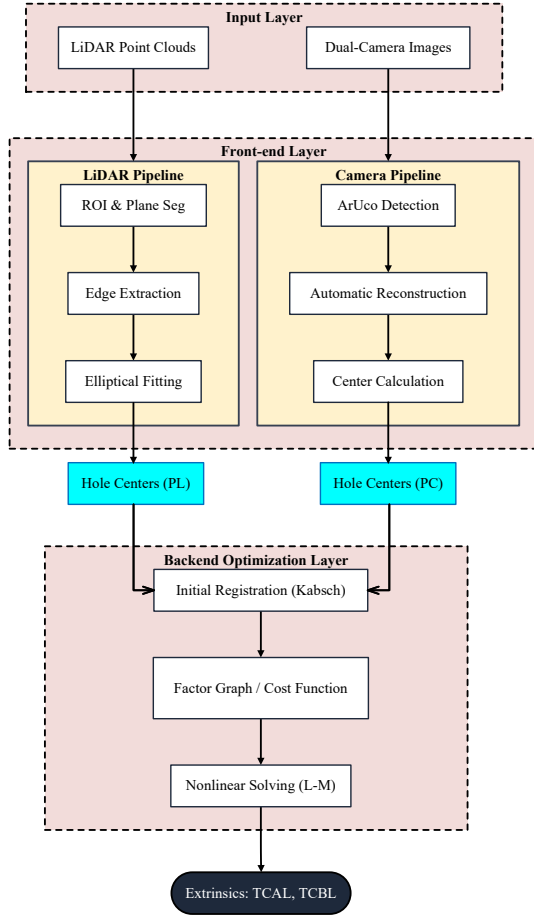


Fig. 1: DUAL-Calib for LiDAR-dual-camera extrinsic calibration

2.2 Automatic Estimation of Target Parameters

Traditional calibration targets require precise manufacturing and manual measurement of feature positions [5, 6, 9]. An alternative approach employs checkerboards with known dimensions, but this method is sensitive to changes in LiDAR reflectivity. AprilCal [14] enables automatic target detection, yet it primarily focuses on camera intrinsic parameters rather than LiDAR-camera extrinsic parameters. This paper combines ArUco marker detection [15] with geometric optimization to automatically solve for target dimensions, eliminating the need for precisely manufactured boards or manual measurements, and it is compatible with LiDAR circular hole features.

3 METHODOLOGY

3.1 Overview

As shown in Fig. 1, DUAL-Calib extends the FAST-Calib process to a dual-camera configuration. The calibration target is identical to that described in Reference [9], consisting of four circular holes and four ArUco markers with known relative positions. However, unlike Reference [9], where these positions must be manually input, the method proposed in this paper can automatically reconstruct the target coordinate system from the detected markers. The data processing flow is divided into two parallel branches:

For LiDAR data, the processing steps of FAST-Calib are adopted, including rough ROI (Region of Interest) extraction, plane segmentation, edge extraction of circular holes, and elliptical fitting compensation. This yields the four hole centers $\mathcal{P}_L = \{\mathbf{p}_i^L\}_{i=1}^4$ in the LiDAR coordinate system $\mathcal{F}_L$.

For camera data, two images are processed simultaneously. Each camera detects ArUco markers and estimates the marker pose via the PnP (Perspective-n-Point) algorithm. Instead of using preset target sizes, this paper directly reconstructs the calibration plate coordinate system $\mathcal{F}_B$ from the marker corner points, and then calculates the corresponding hole centers $\mathcal{P}_{CA}$ and $\mathcal{P}_{CB}$. Finally, through joint geometric registration, the extrinsic transformations T_{CAL} and T_{CBL} are estimated, and rigid constraints between the two cameras can be selectively applied.

3.2 Automatic detection of target corner points

ArUco Corner Triangulation : For each detected marker $m \in \{1, 2, 3, 4\}$, four image corner points $\mathbf{u}_{m,n} \in \mathbb{R}^2$ ($n = 1, \dots, 4$) are acquired. Given the camera intrinsic parameters $\mathbf{K}$ and distortion coefficients, the marker pose $T_{CM_m} \in SE(3)$ is solved using the PnP (Perspective-n-Point) algorithm. The marker corner points in the camera coordinate system are expressed as:

$$\mathbf{P}_{m,n}^C = T_{CM_m} \cdot \mathbf{p}_{m,n}^{M_m}, \quad \mathbf{p}_{m,n}^{M_m} = [\pm s/2, \pm s/2, 0]^T \quad (1)$$

Here, s denotes the known marker size (e.g., 80 mm), and the superscript M_m indicates the local coordinate system of the marker.

Calibration Plane Fitting : Using the 16 triangulated corner points from each camera (4 markers $\times$ 4 corners), the calibration plate plane is fitted. The RANSAC algorithm is employed for robust estimation of the plane parameters $(\mathbf{n}, d)$ in the camera coordinate system, which is defined as:

$$\Pi : \mathbf{n}^T \mathbf{x} + d = 0, \quad \|\mathbf{n}\| = 1 \quad (2)$$

Here, $\mathbf{n}$ represents the normal vector of the plane, and d denotes the distance from the camera coordinate origin to the plane.

Reconstruction of Target Coordinate System : The target coordinate system $\mathcal{F}_B$ is established with the center of the calibration plate as the origin. Let $\mathbf{c}_m$ be the projection of the marker center onto the plane Π . The standard orthogonal basis $\mathbf{e}_x, \mathbf{e}_y$ of the plane is solved by minimizing the following objective function:

$$\min_{\mathbf{e}_x, \mathbf{e}_y, \mathbf{o}_b} \sum_{m=1}^4 \|\mathbf{c}_m - \mathbf{o}_b - u_m \mathbf{e}_x - v_m \mathbf{e}_y\|^2 \quad (3)$$

Subject to the constraints:

$$\mathbf{e}_x^T \mathbf{e}_y = 0, \quad \|\mathbf{e}_x\| = \|\mathbf{e}_y\| = 1, \quad \mathbf{e}_x \times \mathbf{e}_y = \mathbf{n}$$

Here, (u_m, v_m) represents the nominal positions of the markers in the target coordinate system (as shown in Fig. 1 of Reference [9], the standard calibration plate has a horizontal deviation of ± 650 mm and a vertical deviation of ± 450 mm). A closed-form solution to this optimization problem can be obtained via Singular Value Decomposition (SVD) of the centered marker coordinates.

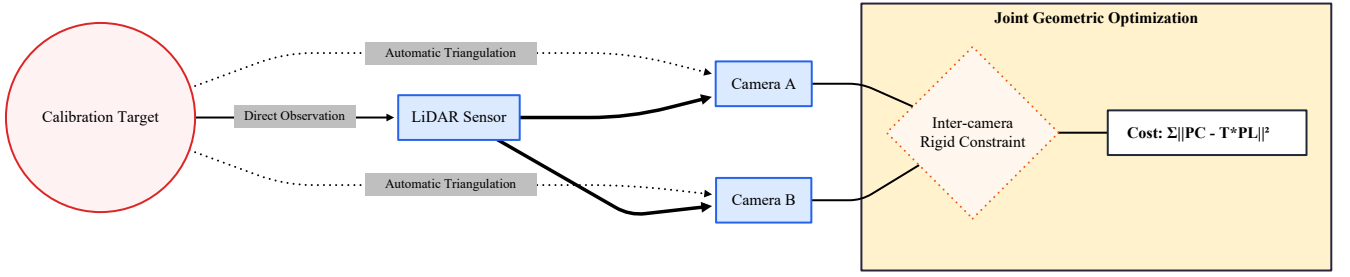


Fig. 2: Joint geometric optimization framework for multi-sensor LiDAR and dual-camera calibration

Center Calculation : After establishing $\mathcal{F}_B$, the center of each circular hole is calculated based on the standard geometry of the calibration plate. For the i -th hole with design coordinates $\mathbf{p}_{h,i}^B = [x_i, y_i, 0]^T$ in the target coordinate system, its coordinates in the camera coordinate system are:

$$\mathbf{p}_{h,i}^C = \mathbf{o}_b + x_i \mathbf{e}_x + y_i \mathbf{e}_y \quad (4)$$

The transformation matrix from the calibration plate coordinate system to the camera coordinate system is:

$$T_{CB} = \begin{bmatrix} \mathbf{e}_x & \mathbf{e}_y & \mathbf{n} & \mathbf{o}_b \\ \mathbf{0}^T & \mathbf{0}^T & \mathbf{0}^T & 1 \end{bmatrix} \quad (5)$$

Cross-camera Verification : For a dual-camera system, the consistency of the reconstruction results is verified by comparing the distances between the marker centers obtained from the two cameras is the core of the joint geometric optimization framework in Fig. 2. The rigid baseline $T_{C_A C_B}$ (transformation from camera C_B to camera C_A) should satisfy the following condition:

$$\|\mathbf{p}_m^{C_A} - T_{C_A C_B} \mathbf{p}_m^{C_B}\| < \epsilon_{consist}, \quad \forall m \quad (6)$$

Herein, the consistency threshold $\epsilon_{consist}$ is set to 0.5 mm, which represents the maximum allowable 3D Euclidean distance deviation of the marker center coordinates reconstructed by the two cameras, and the value is determined based on the sub-millimeter accuracy of the ArUco marker triangulation.

If this condition is not satisfied, rechecking or manual intervention is required. This verification step ensures the reliability of the automatically extracted features before performing geometric registration.

The actual implementation effects of the proposed corner detection algorithm on the left and right cameras are shown in Fig. 3(a) and Fig. 3(b), respectively, which directly reflect the accuracy of ArUco marker triangulation in practical corner extraction.

3.3 Joint Dual-Camera Registration

Given the LiDAR hole center set P_L , dual-camera hole center sets P_{C_A} and P_{C_B} , and the pre-calibrated inter-camera rigid transformation $T_{C_A C_B}$ (from C_B to C_A), this section constructs the LiDAR-dual-camera joint calibration problem with the rigid baseline as the core constraint. The method includes two core modules: independent registration for initial values and constrained joint optimization for high-precision extrinsic parameters, with detailed elaboration on its implementation steps and computational complexity. The full pseudocode of the method is presented in Algorithm 1.

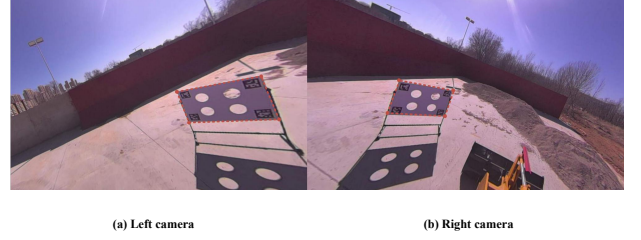


Fig. 3: Automatic calibration board corner point identification via ArUco marker triangulation. (a) Left camera. (b) Right camera.

3.3.1 Independent Registration: Initial Value Solution

Independent registration provides initial LiDAR-to-camera extrinsic parameters for subsequent joint optimization, preventing the latter from falling into local optima. Two independent Kabsch problems are solved via Singular Value Decomposition (SVD) to calculate the initial transformation matrices $T_{C_A L}^o$ and $T_{C_B L}^o$, with the formula:

$$T_{kL}^o = \arg \min_{T \in SE(3)} \left(\sum_{j=1}^N \sum_{i=1}^4 \|p_{i,j}^{C_k} - T p_{i,j}^L\|^2 \right), \quad k \in \{A, B\} \quad (7)$$

where N is the number of calibration scenarios, $p_{i,j}^{C_k}$ and $p_{i,j}^L$ denote the i -th hole center in the j -th scenario under the camera k and LiDAR coordinate systems, respectively.

3.3.2 Constrained Joint Optimization: High-Precision Extrinsic Estimation

Using the initial transformation matrices as iterative starting values, the inter-camera rigid constraint is introduced as the core condition. The Levenberg-Marquardt (L-M) algorithm minimizes the global point-to-point registration error for iterative update, until the results meet the convergence criterion, to achieve high-precision extrinsic parameter estimation.

1) Original Constraint Form : The original method introduces a regularization term to constrain dual-camera pose consistency and ensure physical rationality of calibration results, defined as:

$$\mathcal{R} = \left\| \log \left((T_{C_B L} T_{C_A L}^{-1})^{-1} T_{C_A C_B} \right)^\vee \right\|^2 \quad (8)$$

2) *Simplified Engineering Implementation* : Equation (8) is a soft constraint suitable for noisy baseline conditions. For rigid construction machinery platforms, the inter-camera baseline $T_{C_A C_B}$ is pre-calibrated with high accuracy and can be treated as an exact known constant. We therefore use a hard constraint implementation for efficiency and stability. Only $T_{C_{AL}}$ is optimized, and $T_{C_{BL}}$ is directly derived by $T_{C_{BL}} = T_{C_A C_B} T_{C_{AL}}$. The core objective is to minimize the global point-to-point error:

$$\mathcal{E} = \sum_{k \in \{A, B\}} \frac{1}{4N} \sum_{j=1}^N \sum_{i=1}^4 \left\| p_{i,j}^{C_k} - T_{C_k L} p_{i,j}^L \right\|^2 \quad (9)$$

This simplification reduces computation while ensuring physical consistency, and experiments show it achieves optimal accuracy.

3.3.3 Complete Implementation Steps

The inter-camera rigid transformation $T_{C_A C_B}$ is pre-calibrated offline using Zhang's camera calibration method [16], with translation error better than 0.5 mm and rotation error better than 0.1° . It is treated as an accurate known constant on rigid engineering platforms.

Combining the above two core steps of independent registration and constrained joint optimization, the complete implementation steps of the dual-camera joint registration method can be divided into four sequential and closely linked steps to ensure the integrity and rigor of the calibration process. First, initial values are calculated by solving $T_{C_{AL}}^\circ$ and $T_{C_{BL}}^\circ$ via independent Kabsch-SVD registration; followed by variable initialization, where $T_{C_{AL}}^\circ$ is assigned to the optimization variable $T_{C_{AL}}$. The third step is iterative optimization, which involves cycling parameter derivation and variable update until convergence: specifically, $T_{C_{BL}}$ is derived from the current $T_{C_{AL}}$ using the formula $T_{C_{BL}} = T_{C_A C_B} T_{C_{AL}}$, and then $T_{C_{AL}}$ is updated by minimizing $\mathcal{E}$ with the L-M algorithm.

The final step is result output: the optimal $T_{C_{BL}}^* = T_{C_A C_B} T_{C_{AL}}^*$ is calculated from the converged $T_{C_{AL}}^*$, and then the optimal extrinsic parameters $T_{C_{AL}}^*$ and $T_{C_{BL}}^*$ are outputted, along with the final registration error $\mathcal{E}^*$ and the number of iterations performed. Additionally, the satisfaction of the rigid constraint is verified by checking the condition :

$$\|T_{C_{BL}}^* (T_{C_{AL}}^*)^{-1} - T_{C_A C_B}\| < \epsilon_{rigid} \quad (10)$$

where the rigid constraint threshold ϵ_{rigid} is defined by two quantitative indicators: the translation deviation < 0.5 mm and the rotation deviation $< 0.1^\circ$ between the relative pose calculated by the calibrated extrinsic parameters and the pre-calibrated inter-camera rigid transformation, which is consistent with the experimental accuracy results of the dual-camera relative pose.

3.3.4 Computational Complexity Analysis

Quantitative analysis of computational complexity verifies the method's real-time performance, considering matrix operations and iteration times:

Algorithm 1 Simplified LiDAR-Dual-Camera Joint Registration

Require: $\mathcal{P}_L, \mathcal{P}_{C_A}, \mathcal{P}_{C_B}, T_{C_A C_B}, \epsilon = 1 \times 10^{-6}$

Ensure: $T_{C_{AL}}, T_{C_{BL}}$

Independent Registration (Kabsch-SVD)

1: Compute $T_{C_{AL}}^\circ$ and $T_{C_{BL}}^\circ$ separately using SVD.

Constrained Joint Optimization

2: Initialize $T_{C_{AL}} \leftarrow T_{C_{AL}}^\circ$

3: **while** not converged **do**

4: Derive $T_{C_{BL}} = T_{C_A C_B} T_{C_{AL}}$

5: Compute point-to-point loss $\mathcal{E}$

6: Update $T_{C_{AL}}$ by L-M algorithm

7: Check convergence: $\|\Delta T_{C_{AL}}\| < \epsilon$

8: **end while**

9: **Output**

10: $T_{C_{BL}} \leftarrow T_{C_A C_B} T_{C_{AL}}$

11: **return** $T_{C_{AL}}, T_{C_{BL}}$

1. Independent registration: Two SVD operations on fixed 3x3 covariance matrices ($O(1)$ for a single SVD), with an overall complexity of $O(N)$ due to summation of corresponding points across N scenarios.

2. Constrained joint optimization: Convergence within a fixed number of iterations C (5-10 in engineering), with $8N$ residual calculations per iteration, leading to a complexity of $O(C \cdot N) = O(N)$.

3. Overall complexity: The total time complexity of the method is $O(N)$, ensuring the entire DUAL-Calib framework runs in less than 1 second and meets the requirements of rapid on-site engineering calibration.

The full pseudocode of the proposed method is shown in Algorithm 1.

4 EXPERIMENT

4.1 Implementation Details

Calibration tests were conducted on a wheel loader for real engineering scenarios, with the Lingmou S1 module (1 Livox Mid-360 LiDAR + 2 global-shutter fisheye cameras, 1920x1200@10 Hz) as the core hardware. Fig. 4 shows the structural composition of the Lingmou S1 module, presenting the integrated layout of the Livox Mid-360 LiDAR and two wide-angle fisheye cameras in the module. All sensors were rigidly mounted on the loader cab to maintain fixed relative poses for vibration and bumping resistance. A 3D calibration target identical to FAST-Calib (4 circular holes + 4 ArUco markers) was randomly placed in the overlapping sensor FOV (1.5–4.5 m from the loader) to simulate unstandardized on-site layouts. Fig. 5 shows the actual experimental scene of the LiDAR-dual-camera calibration on the wheel loader, including the mounting position of the Lingmou S1 module on the cab and the placement of the 3D calibration target in the working area. Experiments were run on an industrial embedded host (Intel i7-12700H, 32 GB RAM) with C++/OpenCV/PCL-based software. Camera intrinsic and distortion parameters were pre-calibrated via Zhang's method [16] to eliminate intrinsic errors.

4.2 Comparison with FAST-Calib

Field tests were conducted on the loader under illumination variation, ground vibration and background clutter, comparing DUAL-Calib's dual-camera results with FAST-

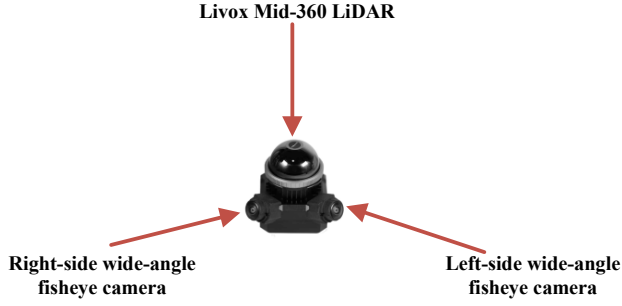


Fig. 4: Structural composition of the Lingmou S1 module for LiDAR-dual-camera perception



Fig. 5: Actual experimental scene of LiDAR-dual-camera extrinsic calibration on a wheel loader

Table 1: LiDAR-Dual-Camera Registration Error and Processing Time: DUAL-Calib vs. FAST-Calib

Calibration Method	LiDAR-Camera A (Mean $\pm$ Std)(mm)	LiDAR-Camera B (Mean $\pm$ Std)(mm)	Overall Processing Time (s)
FAST-Calib	7.2 $\pm$ 1.8	7.5 $\pm$ 2.1	0.68 $\pm$ 0.05
DUAL-Calib	4.5 $\pm$ 0.7	4.8 $\pm$ 0.8	0.85 $\pm$ 0.06

Calib's independent single-camera calibration. 10 sets of calibration data with different target poses were collected for each method, and the point-to-point registration errors of LiDAR-Camera A/B were calculated.

Table 1 shows the results, where FAST-Calib adopted independent calibration and DUAL-Calib used a joint optimization framework with dual-camera rigid-body constraints. DUAL-Calib's mean errors for LiDAR-Camera A/B were both within 5.0 mm, reduced by 37.5% and 36.0% compared with FAST-Calib, with significantly lower variance. The rigid-body constraints effectively mitigated environmental interference and improved robustness. DUAL-Calib's overall processing time was 0.85 s (slightly longer than FAST-Calib's 0.68 s due to joint optimization), still within 0.9 s and meeting on-site rapid calibration requirements.

4.3 Auto vs. Manual Target Feature Acquisition

To verify the accuracy of the proposed automatic calibration board corner detection algorithm, the 3D coordinates of calibration board corners manually annotated by profession-

Table 2: Error Statistics of the Automatic Calibration Board Corner Detection Algorithm

Camera Type	Maximum Deviation (cm)	Mean Deviation (cm)	Standard Deviation (cm)
Left Camera	0.26	0.11	0.03
Right Camera	0.28	0.13	0.04
Overall	0.28	0.12	0.03

als are adopted as the reference ground truth for comparative experiments. The manually annotated corner coordinates are required to satisfy the mechanical design geometric constraints of the calibration board (e.g., the deviation between the distance of adjacent corners and the nominal value is less than 1 mm), which ensures the reliability of the reference ground truth for subsequent comparison. In the experiment, the deviation of automatic detection is defined as the 3D Euclidean distance between the 3D corner coordinates output by the algorithm and the reference ground truth. The experimental data of 10 groups of different calibration scenarios were statistically analyzed, and the results are shown in Table 2.

It can be seen from Table 2 that the maximum deviation of the proposed automatic detection algorithm on the left and right cameras is less than 0.3 cm, and the mean deviation is only 0.11 ~ 0.12 cm, indicating that the algorithm can achieve high-precision automatic corner extraction with an extremely low error level.

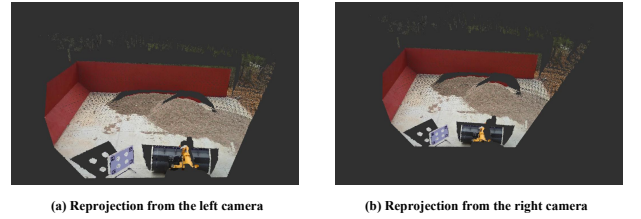


Fig. 6: Re-projection verification of the DUAL-Calib calibration effect for LiDAR-dual-camera extrinsic parameters

4.4 Consistency and Robustness

Based on 10 repeated calibration data sets, the relative pose deviation of dual-camera results was calculated to verify the effectiveness of DUAL-Calib's joint optimization constraints and rigid-body compliance. To further visually evaluate the calibration accuracy and analyze the re-projection error distribution, the re-projection verification and error statistical analysis of the calibration effect are carried out, and the result is shown in Fig.6.

Reprojection error is used as a supplementary quantitative metric: the mean reprojection error is 0.32 pixels for the left camera and 0.35 pixels for the right camera, both below the subpixel level, and the maximum reprojection error of both cameras is controlled within 0.5 pixels, with the error fluctuation range less than 0.15 pixels, which verifies the high precision and stability of the proposed method.

DUAL-Calib's robustness was also tested under loader vibration conditions (Idle and low-speed driving conditions with a speed of ≤ 5 km/h). The results showed that DUAL-Calib's LiDAR-camera extrinsic parameters converted to Camera A-B relative pose had translation deviation < 0.5 mm and rotation deviation $< 0.1^\circ$, satisfying rigid-body constraints. In contrast, FAST-Calib's independent mode had

obvious inconsistency, with maximum translation/rotation deviations of 2.3 mm and 0.5°. Under vibration conditions, DUAL-Calib's mean registration error remained within 5.8 mm with no significant increase, indicating strong robustness to vibration and illumination variations in engineering scenarios.

5 CONCLUSIONS

We present DUAL-Calib, a joint extrinsic calibration framework for LiDAR-dual-camera systems, an optimized extension of FAST-Calib for multi-camera scenarios. It builds a unified optimization model with inter-camera rigid geometric constraints and an ArUco marker triangulation-based automatic target corner detection algorithm that dispenses with manual target measurement. Adopting Kabsch-SVD initial registration and L-M constrained joint optimization, the framework achieves an overall time complexity of $O(N)$.

Experimental validations are conducted on a wheel loader platform equipped with the Lingmou S1 module (a Livox Mid360 LiDAR plus two wide-angle fisheye cameras). The results show that DUAL-Calib outperforms FAST-Calib, with mean registration errors below 5.0 mm for both camera channels, representing an accuracy improvement of over 36%. Its automatic corner detection achieves sub-millimeter precision with a maximum deviation of only 0.28 cm, and the error remains under 5.8 mm even under vibration interference. The framework strictly satisfies inter-camera rigid constraints and has an overall processing time of less than 0.9 seconds, enabling rapid on-site calibration.

DUAL-Calib's core contributions include a rigid-constrained unified joint optimization framework for dual cameras, semi-automated target feature extraction with reduced manual measurement, and a field-deployable calibration pipeline with high robustness and low complexity. It resolves the cumulative error issue of independent single-camera calibration, bridges the practicality gap between laboratory calibration and the on-site deployment of construction machinery, and delivers notable engineering application value.

Future work will extend the framework to multi-camera systems, enhance its robustness in extreme engineering environments, integrate an IMU for dynamic online calibration, conduct lightweight optimization for edge device deployment, and expand its compatibility to support the joint calibration of multi-modal sensors.

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