Joint Calibration Method for Moving Camera and LiDAR Based on LM Algorithm (Postprint)

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Abstract

To solve the data alignment problem between moving cameras and LiDAR, a joint calibration optimization method based on the Levenberg-Marquardt (LM) algorithm is designed for moving cameras and LiDAR. Initially, the calibration target is placed within the common field of view of the LiDAR and moving camera, and LiDAR point clouds and image data of the calibration object are acquired at various positions by altering the target's location. Subsequently, OpenCV is utilized to invoke fisheye distortion correction functions for image rectification, and multiple sets of corner pixel coordinates from the calibration target images are extracted. Concurrently, point cloud filtering and registration operations are performed on the LiDAR point clouds, and a hybrid manual-automatic approach is employed to segment the LiDAR point clouds, thereby solving for the calibration target's point cloud center coordinates and the point cloud coordinates of each corner through a point cloud center iterative algorithm. Finally, using multiple sets of point cloud coordinates representing the calibration target corners and their corresponding image pixel coordinates, the Direct Linear Transformation (DLT) method is applied to compute the initial joint calibration parameters between the two sensors, and a least squares function of the residuals between point cloud reprojection coordinates and image pixel coordinates is constructed. This function is optimized through the LM algorithm with an introduced damping factor, yielding the refined joint calibration result. Experimental results indicate that the reprojection error is reduced by 35% compared to the initial value. The accuracy and effectiveness of the proposed method are validated by fusing LiDAR point clouds with images based on the collinearity equation principle.

Full Text

A Joint Calibration Optimization Method for Sports Cameras and LiDAR Based on the Levenberg-Marquardt Algorithm

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Abstract

To address the data matching problem between sports cameras and LiDAR, this paper proposes a joint calibration optimization method based on the Levenberg-Marquardt (LM) algorithm. The calibration board is first placed within the common field of view of the LiDAR and sports camera, and multi-group laser point cloud and image data of the calibration target are collected by changing the board's position. The OpenCV library is used to call the fisheye distortion correction function for image rectification, and multiple sets of pixel coordinates for the calibration board's corner points are obtained from the corrected images. Simultaneously, the laser point clouds undergo filtering and registration operations, and a combined manual-automatic method is employed to segment the LiDAR point clouds. An iterative point cloud center algorithm is then used to solve for the calibration board's point cloud center coordinates and the point cloud coordinates of each corner point. Finally, using multiple sets of point cloud coordinates representing the calibration board corners and their corresponding image pixel coordinates, the direct linear transformation (DLT) method calculates the initial joint calibration value between the two sensors. A least-squares function is constructed based on the difference between the reprojected point cloud coordinates and the image pixel coordinates, and the LM algorithm with a damping factor is introduced to optimize this function and obtain the refined joint calibration result. Experimental results demonstrate that compared with the initial value, the joint calibration result reduces reprojection error by approximately 40%, thereby verifying the accuracy and effectiveness of the proposed method. Using the optimized joint calibration result, laser point cloud and image fusion is achieved based on the collinearity equation principle.

Keywords: sports camera; LiDAR; joint calibration; Levenberg-Marquardt algorithm; image distortion correction; direct linear transformation; least squares method; OpenCV

1. Introduction

Multi-sensor systems composed of sports cameras and 3D LiDAR serve as crucial technical means for indoor scene 3D reconstruction and outdoor digital photogrammetry, and are currently being widely researched and applied. Image data contains rich color and texture information, while laser point cloud data provides high-precision 3D positional information of objects. Fusing these two data types can optimize indoor environment 3D reconstruction. Since data collected by the two sensors are represented in their respective coordinate systems, accurately obtaining the joint calibration parameter matrix between the sensors is essential for effective data fusion.

Joint calibration between the two sensors utilizes corresponding corner points on the calibration board to construct parameter equations from 3D LiDAR point cloud coordinates and 2D image coordinates, thereby solving for the joint calibration matrix. Existing methods include target-based and targetless approaches. Ishikawa et al.[1] propose a targetless calibration method using lines and planes as features, which avoids mixed-pixel phenomena. Kang et al.[2] present a targetless approach for precise estimation of camera-LiDAR rigid transformation by minimizing an edge alignment cost function across sensors. Huang et al.[3] propose a method to determine LiDAR-camera external calibration using a specially shaped calibration object to reduce LiDAR quantization and systematic errors. Zheng et al. utilize correspondence between chessboard plane data in camera and LiDAR coordinate systems to project LiDAR point clouds onto corresponding image corners, converting external parameter calibration into a 3D rotation and scaling matrix problem. Yu et al. use ArUco markers to establish relationships between calibration boards in LiDAR and camera coordinate systems, extracting corner coordinates through RANSAC and solving registration parameters via the Kabsch algorithm. Wei et al. replace LiDAR with a single-point laser rangefinder and solve for high-precision external parameter matrices using collinearity equations. Ke et al. propose a reprojection error-based calculation method and optimize target placement to reduce random positioning effects on joint calibration. However, the accuracy of these joint calibration parameters remains to be improved.

Building upon existing research, this paper optimizes joint calibration between sports cameras and 3D LiDAR by proposing an LM algorithm-based optimization method. Through practical joint calibration experiments, the accuracy and effectiveness of the optimization method are verified, providing a foundation for laser point cloud and image data fusion and advancing digital photogrammetry.

2. Methodology

2.1 Joint Calibration Model The transformation between the sports camera coordinate system and the LiDAR coordinate system is illustrated in [Figure 1: see original paper]. Let $O_cX_cY_cZ_c$ denote the camera coordinate system and $O_lX_lY_lZ_l$ denote the LiDAR coordinate system. R and T represent the rotation matrix and translation matrix between the two coordinate systems, respectively, forming the joint calibration parameter matrix M between the sports camera and LiDAR sensor.

According to the pinhole camera model principle, sports cameras are ultra-wide-angle cameras that exhibit certain distortion. The relationship between a 3D point P in local space coordinates and its projection p in image pixel coordinates is given by:

$$s\begin{bmatrix}u\\v\\1\end{bmatrix} = M_1\begin{bmatrix}R & T\\0 & 1\end{bmatrix}\begin{bmatrix}X\\Y\\Z\\1\end{bmatrix} = M_1M_2P = MP$$

where s is a scaling factor, M_1 is the camera intrinsic matrix, M_2 represents the transformation from local 3D space to camera coordinate system, and M denotes the combined rotation-translation matrix from local space to image pixel coordinates.

2.2 Image Distortion Correction Ultra-wide-angle sports cameras produce significant image distortion requiring correction. Based on the OpenCV fisheye camera distortion correction principle, the process involves:

1. Converting pixel coordinates (u, v) to normalized coordinates (x, y) in the image plane coordinate system
2. Transforming to polar coordinates (r, θ) in the fisheye hemispherical model, where $r^2 = u^2 + v^2$
3. Applying the distortion model: $\theta_d = \theta(1 + k_1\theta^2 + k_2\theta^4 + k_3\theta^6 + k_4\theta^8)$, where k_1 through k_4 are distortion parameters
4. Reprojecting 3D space points to the 2D image plane to obtain corrected coordinates (u', v')
5. Assigning color values via bilinear interpolation to generate the final distortion-corrected calibration board image

2.3 LiDAR Point Cloud Preprocessing After LiDAR data acquisition, preprocessing is essential for accurate joint calibration. The preprocessing pipeline includes point cloud filtering, segmentation, and calculation of calibration board center and corner coordinates.

Point Cloud Filtering: Removes noise and outlier points from the scene point cloud. The filtered point cloud provides a cleaner dataset for subsequent operations.

Point Cloud Segmentation: A manual-automatic hybrid approach segments the target scene. Using PolyWorks software, the original 3D laser point cloud is manually segmented to extract the calibration board region. The K-means clustering algorithm then automatically processes the segmented point cloud to obtain a clean calibration board point cloud with clear boundaries.

Iterative Center Algorithm: This algorithm accurately determines the calibration board's point cloud center and corner coordinates while reducing outlier effects by iteratively shrinking the point cloud spatial range. For point cloud set $Q = \{q_1, q_2, \ldots, q_k\}$:

1. Calculate initial center: $\bar{q} = \frac{1}{k}\sum_{i=1}^{k} q_i$
2. Compute total distance: $D = \sum_{i=1}^{k} \|q_i - \bar{q}\|$
3. Update point cloud: $Q' = \{q_i' \mid q_i' = q_i - \frac{q_i - \bar{q}}{D}\}$
4. Recalculate center: $\bar{q}' = \frac{1}{k}\sum_{i=1}^{k} q_i'$
5. Iterate until $\|\bar{q}' - \bar{q}\| < \epsilon_q$ (threshold)

After obtaining the center, corner coordinates are calculated based on the calibration board's physical dimensions and grid pattern.

2.4 Direct Linear Transformation for Initial Calibration The direct linear transformation (DLT) method constructs multiple linear equations using corresponding corner point cloud coordinates and image pixel coordinates. For each correspondence, the relationship is:

$$\begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} \sim M \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix}$$

where (u_i, v_i) are image coordinates and (X_i, Y_i, Z_i) are LiDAR coordinates of the i-th corner. Solving these equations yields the initial joint calibration matrix $M_{initial}$.

2.5 LM Optimization Algorithm The Levenberg-Marquardt algorithm is a proven method for solving nonlinear least-squares problems. After obtaining the initial calibration matrix, the algorithm optimizes it by minimizing the reprojection error:

$$f = \sum_{i=1}^{n} \left[(x_i - u_i)^2 + (y_i - v_i)^2\right]$$

where (x_i, y_i) are reprojected coordinates and (u_i, v_i) are actual image coordinates.

The LM algorithm improves upon Gauss-Newton by introducing a damping factor μ to control step size:

$$d_k = -(J(x_k)^T J(x_k) + \mu I)^{-1} J(x_k)^T F(x_k)$$

where J is the Jacobian matrix and I is the identity matrix. When μ is large, the step approaches gradient descent; when small, it approaches Gauss-Newton. The algorithm iteratively updates the calibration parameters until convergence.

3. Experiments

3.1 Experimental Setup Experiments were conducted using a Velodyne VLP-16 LiDAR and a GoPro Hero5 Session camera. The detailed parameters are listed in and .

TABLE 1: VLP-16 LiDAR Parameters - Laser beams: 16 - Range: 0-100 m - Horizontal FOV: 360° - Vertical FOV: -15° to +15° - Angular resolution: 0.1° to 0.4°

TABLE 2: GoPro Hero5 Session Parameters - Resolution: 736 × 3 (appears incomplete in original)

The camera intrinsic parameters were first calibrated using Zhang's method through MATLAB's calibration toolbox, with results shown in .

TABLE 3: Camera Intrinsic Parameters - Focal length: f_u, f_v (values not fully specified in original) - Principal point: (u_0, v_0) - Distortion coefficients: k_1, k_2, k_3, k_4

3.2 Calibration Procedure A planar chessboard calibration board (32 cm × 32 cm) was placed in the common FOV of both sensors. To improve calibration accuracy: 1. The board position was varied to maximize LiDAR points on its surface 2. The distance between board and sensors was maintained at approximately 2 meters 3. Clear images were captured for corner detection via OpenCV 4. Multiple datasets were collected at different board positions symmetric about the camera's optical axis

3.3 Data Preprocessing **Image Preprocessing**: Distortion correction was applied using the camera model, with before/after comparison shown in [Figure 2: see original paper].

Point Cloud Preprocessing: - Filtering removed outliers and noise ([Figure 3: see original paper]) - Since static scenes were captured, no point cloud registration was needed - Manual-automatic segmentation isolated the calibration board ([Figure 4: see original paper]) - K-means clustering automatically processed the segmented point cloud - The iterative center algorithm computed precise board center and corner coordinates ([Figure 5: see original paper])

4. Results and Discussion

Using the intrinsic matrix and multiple sets of corner coordinates from both modalities, DLT constructed and solved linear equation groups to obtain the initial joint calibration matrix. The LM algorithm then optimized this initial value.

TABLE 4: Calibration Results Comparison | Parameter | Initial Value | Optimized Value | Improvement | |———–|—————|—————-|————-| | Reprojection Error | Baseline | Reduced by ~40% | 40% reduction | | Horizontal

Error | Baseline | Reduced by X% | Significant | | Vertical Error | Baseline | Reduced by Y% | Significant |

The reprojection error after LM optimization decreased by approximately 40% compared to the initial DLT result. [Figure 6: see original paper] shows corner detection (blue circles) and reprojected LiDAR points (red circles) on the calibration board image, demonstrating improved alignment after optimization.

[Figure 7: see original paper] compares point cloud reprojection before and after optimization, showing clearer and more accurate projection of LiDAR points onto the calibration board.

5. 3D Reconstruction Application

Using the optimized joint calibration result and collinearity equations, laser point clouds were fused with image data for 3D reconstruction. The homography between image pixels and point clouds was computed, assigning RGB values from image pixels to corresponding 3D points. [Figure 8: see original paper] demonstrates the 3D indoor environment reconstruction result, validating the method's effectiveness for practical applications.

6. Conclusion

This paper presents an LM algorithm-based optimization method for joint calibration of sports cameras and LiDAR. The approach combines DLT for initial calibration with LM optimization for refinement. Experimental results show that: 1. The method reduces reprojection error by ~40% compared to initial calibration 2. The iterative center algorithm accurately extracts calibration board features 3. The manual-automatic segmentation approach effectively isolates target point clouds 4. Optimized calibration enables high-quality 3D reconstruction through point cloud-image fusion

The proposed method provides an accurate and effective solution for multi-sensor calibration, contributing to advancements in digital photogrammetry and 3D reconstruction applications.

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Note: Figure translations are in progress. See original paper for figures.