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Fused Complementary 3D Reconstruction Based on Polarization Binocular Line-Structured Light

Mingsheng Liu ¹, Hongyuan Zhou ¹, Sisheng Nie ², Yan Jiang ¹, Zhong Wu ³, Dahai Xu ³, Ling Zhu ⁴, Yanliang Zhan ² and Zhenmin Zhu ^{2,*}

¹ Jiangxi Traffic Monitoring Command Center, Nanchang 330036, China

² School of Electrical and Electronic Engineering, East China Jiaotong University, Nanchang 330013, China

³ Jiangxi Fangxing Technology Co., Ltd., Nanchang 330025, China

⁴ Jiangxi Communications Design and Research Institute Co., Ltd., Nanchang 330001, China

* Correspondence: 2707@ecjtu.edu.cn

Abstract

Line-structured light three-dimensional (3D) measurement is commonly used for three-dimensional contour reconstruction of objects in complex industrial environments, but the problem of missing information occurs when three-dimensional reconstruction is performed on objects with smooth surfaces, single texture, and high reflectivity, resulting in defective reconstructed object surfaces. For this reason, this study proposes a fused complementary 3D reconstruction technique based on a polarization-based binocular line-structured light system. First, the reconstructed image of the object is captured using a Polarization Binocular Camera, and the polarized imaging effectively reduces the strong highlights and extracts more detailed information on the surface of the object. Then, the calibrated camera and optical planes are used to acquire the spatial coordinates of the object reconstructed by the left camera and right camera. Finally, the spatial coordinates obtained by the left camera and right camera are aligned, and the high-precision 3D reconstruction results are generated. The experimental results show that the proposed method can effectively improve the accuracy and robustness of 3D reconstruction, has a good application prospect, and can meet the technical requirements of industrial 3D measurement.

Keywords: polarization line-structured light; binocular; 3D reconstruction

1. Introduction

Three-dimensional measurement based on multi-view imaging has a long history in photogrammetry and computer vision. As early as the 1980s, automated stereo matching techniques were developed to reconstruct 3D point clouds from overlapping images captured by two or more cameras from different viewpoints [1]. A landmark survey by Mayer in 1988, published under the auspices of the International Society for Photogrammetry and Remote Sensing (ISPRS), provided a comprehensive review of stereo matching algorithms available at the time, many of which laid the foundation for modern 3D reconstruction pipelines [2]. The theoretical and practical framework of digital photogrammetry—formalized over decades by researchers such as Kraus [3], Luhmann et al. [4], and McGlone [5]—has established rigorous methodologies for geometric reconstruction from imagery, forming a cornerstone of non-contact 3D measurement.



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In recent years, advances in structured light projection, high-resolution sensors, and real-time image processing have further enhanced the accuracy, robustness, and applicability of 3D measurement systems—particularly in industrial inspection, reverse engineering, and dynamic scene capture.

In many application fields, such as virtual reality [6], augmented reality [7], industrial measurement [8], etc., accurate and fast acquisition and reconstruction of real-world 3D information has become an important task. Line-structured light 3D reconstruction, as a common 3D reconstruction method, can obtain the 3D shape information of the measured object by projecting light and analyzing its deformation information. It has the advantages of non-contact, fast imaging speed, high measurement accuracy, and a strong sense of reality. It has been widely used in industrial environments [9–11].

In previous decades, various 3D reconstruction methods have been developed to meet the needs in different application scenarios. The traditional 3D reconstruction methods are mainly based on the principles of visual geometry, which mainly include techniques such as stereo vision [12] and structured light [13–16]. Pioneering work by Faugeras [17] and Hartley & Zisserman [18] formalized the geometric foundations of multi-view reconstruction, while Salvi et al. [19] and Geng [20] provided comprehensive surveys of structured light techniques that remain widely cited today. The line-structured light 3D reconstruction method belongs to one kind of structured light technology, which utilizes the principle of light projection and reflection to obtain the depth information on the surface of the measured object. The basic principle of line-structured light 3D reconstruction is that a series of light lines is projected on the surface of the object to be measured, and the deformation of the light lines on the surface of the object is analyzed. The camera acquires the contour image, detects the 2D image coordinates of the structured light stripe, and calculates the corresponding 3D coordinates using the proposed algorithm. The essence of the process of online-structured light 3D reconstruction is how to convert the two-dimensional light stripe coordinate information into three-dimensional coordinate information to infer the depth information of the object surface. Many studies have investigated the line-structured light 3D reconstruction method. For example, Hao et al. [21] proposed a 3D reconstruction technique for pavements based on line-structured light. Chen et al. [22] proposed a monocular line-structured light-based 3D scanning method for large workpieces. A combined monocular and binocular method for scanning line-structured light was used by Wang et al. [23]. The scanning is performed in a binocular system, and iterative eigenvalue least squares are used to fit the 3D point coordinates of the center of the acquired light stripes to obtain the light plane equation. Finally, the obtained light plane equation is utilized in the monocular system to calculate the 3D point coordinates of the object surface based on the geometric principle of perspective projection. Guo et al. [24] built a 3D point cloud measurement system based on a line-structured light sensor and a high-precision air-bearing rotary table. It can quickly obtain the 3D shape information of gears and tooth flanks. Finally, the profile and pitch errors were calculated and evaluated. Wang et al. [25] proposed a monocular camera 3D reconstruction method based on an improved line-structured light marker localization method and the Scheimpflug principle. These structured light 3D reconstruction methods use a scanning system consisting of a camera and a line-structured light emitter. This method is simple in composition and can scan objects quickly. However, some problems are encountered when scanning the surface of complex objects. Occlusions and highlights on the surface of the object itself can cause some information to be lost during the 3D reconstruction process. This means that the 3D shape of the object cannot be recovered accurately and completely. To overcome this occlusion limitation inherent in conventional structured light systems, we integrate a laser line projector with a dual-camera stereo setup. This hybrid configuration leverages geometric redundancy: even

if a surface point is occluded in one camera view, the laser stripe observed by the other camera—combined with the calibrated projector–camera geometry—enables triangulation of the otherwise invisible region.

The structure of this paper is as follows: the first part is the introduction; the second part introduces the line-structured optical vision sensor and the dual-camera model, as well as the transformation between each coordinate system; the third part is the principle of the 3D measurement system; the fourth part is the experimental part, and the experimental results validate the feasibility of the method; and the fifth part is the conclusion.

2. Basic Principles and Models

2.1. Model of the Line-Structured Light Vision Sensor

Aiming at the above problems, the work in this paper is inspired by the line-structured light scanning method based on the combination of monocular and binocular proposed by Wang and the reconstruction method by Hu [26] using an integrated measurement system with multiple line-structured light sensors. A complementary 3D reconstruction technique based on polarized binocular line-structured light fusion is proposed. To obtain a 3D model of the object with richer 3D point cloud data and higher accuracy by one scan. A rotary scanning 3D measurement system was constructed using two CCD cameras with polarizers in front and a laser transmitter. The left and right cameras were combined with the laser to form two measurement systems, i.e., the left camera and the right camera, respectively. And the 3D model of the object with richer point cloud information is obtained through data fusion. In this paper, firstly, the camera and the optical plane are calibrated for the left camera and the right camera, respectively, to obtain the interior and external parameters of the camera and the optical plane equations. After that, the triangulation principle is utilized to obtain the spatial 3D data of the objects to be measured by the left camera and the right camera, respectively. Taking the coordinate system of the left camera as the world coordinate system, the 3D coordinate data under the corresponding camera coordinate system of the right camera are unified into the world coordinate system through the rotation translation matrix of the relative position relationship between the two cameras. Finally, the rotational translation matrix of the left camera is then used to transform all the 3D camera coordinate points to the world coordinate system for point cloud data fusion.

A line-structured light vision sensor contains two main components: a laser and a CCD camera. As shown in Figure 1. The laser generates a beam of light that forms an optical plane that intersects the object to be measured. This light plane projects on the object a light stripe L reflecting the contour of the object. The points on the light stripe L are the points we want to measure, and they are imaged by the camera onto the image plane. By establishing a perspective correspondence between the light plane and the image plane, we can calculate the coordinates of the corresponding measured points in space from the positions of the image points. In Figure 1, O_c is the perspective projection center of the camera, and the image plane O_c of the camera is the distance to the point f called the effective focal length. $O_w X_w Y_w Z_w$ is the world coordinate system (WCS), $O_c X_c Y_c Z_c$ is the camera coordinate system (CCS), and $O_u X_u Y_u$ is the image coordinate system (ICS). The line-structured light vision sensor utilizes the principle of triangular sectioning to obtain the 3D coordinate information on the light bar.

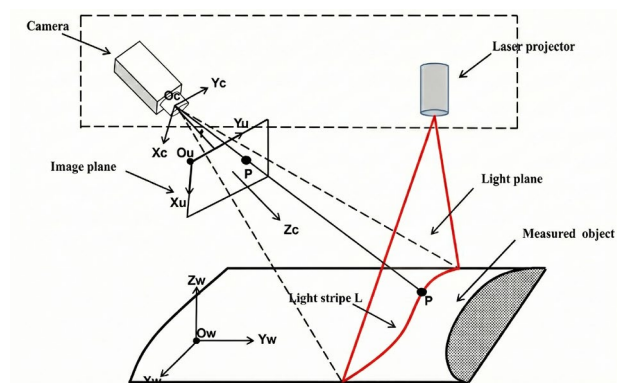


Figure 1. Diagram of the line-structured light 3D measurement model.

An arbitrary point P on the optical plane is assumed to have a projection point p on the image plane, and the point P has the coordinates $P_c(X_c, Y_c, Z_c)^T$ on the camera coordinate system, the point p has the coordinates $P_w(X_w, Y_w, Z_w)^T$ on the world coordinate system, and the corresponding pixel-planar coordinate system is $P(u, v)^T$ on the pixel-planar coordinate system, and the corresponding image coordinate system is $P(X, Y)^T$ on the image coordinate system.

According to the pinhole camera model, the perspective projection from a 3D point in the world coordinate system to its corresponding pixel coordinates in the image plane is given by Equation (1):

$$s \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = N \begin{bmatrix} R & T \\ \vec{0} & 1 \end{bmatrix} \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix} = M \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix} \quad (1)$$

where s is an arbitrary scale factor, N denotes the interior matrix, and R and T represent the rotation and translation between the world and camera coordinate systems, respectively.

R denotes the 3×3 orthogonal rotation matrix, T denotes the 3×1 translation matrix vector, and $\vec{0}$ denotes the 1×3 zero matrix. M is the projection matrix of the camera. N is the matrix of interior parameters of the camera. Defined as Equation (2):

$$N = \begin{bmatrix} f_x & 0 & u_0 & 0 \\ 0 & f_y & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad (2)$$

where f_x and f_y denote the effective focal lengths in the column and row directions of the image sensor, respectively. These two parameters are introduced to account for the possible non-square geometry of the image pixels, which can cause different scaling factors along the image axes. The point (u_0, v_0) denotes the principal point (optical center).

To correct for lens imperfections, we model both radial and tangential distortions using the standard Brown–Conrady distortion model. The relationship between the distorted pixel coordinates (u_d, v_d) and the ideal undistorted coordinates (u, v) is given by Equations (3) and (4):

$$u_d = u + (u - u_0) \left(k_1 r^2 + k_2 r^4 \right) + \left[2p_1 (u - u_0)(v - v_0) + p_2 \left(r^2 + 2(u - u_0)^2 \right) \right] \quad (3)$$

$$u_d = v + (v - v_0) \left(k_1 r^2 + k_2 r^4 \right) + \left[2p_2 (u - u_0)(v - v_0) + p_1 \left(r^2 + 2(v - v_0)^2 \right) \right] \quad (4)$$

where $r^2 = (u - u_0)^2 + (v - v_0)^2$, and k_1, k_2 are radial distortion coefficients, while p_1, p_2 are tangential distortion coefficients.

In this paper, all interior parameters—including $f_x, f_y, u_0, v_0, k_1, k_2, p_1$ and p_2 —are calibrated using Zhang’s method [27], extended with an optimal polarization angle strategy [28], and implemented via the MATLAB Camera Calibrator toolbox (Version R2022a, The MathWorks, Inc., Natick, MA, USA) [29]. The p point satisfies the optical plane equation, and the line-structured light vision sensor utilizes the triangulation principle to obtain 3D coordinate information on the light stripe. The projected light plane equation can be expressed as Equation (5):

$$Z_W = Ax_W + By_W + C \quad (5)$$

The parameters A, B , and C in the light plane equation (Equation (3)) are determined through a calibration procedure using the checkerboard pattern mounted on the rotating platform. Specifically, the laser stripe is projected onto the checkerboard at multiple rotational angles, and the corresponding 3D coordinates of points on the stripe are reconstructed using the calibrated camera model. These 3D points are then fitted to a plane via least-squares regression to obtain A, B , and C .

The model parameters of the line-structured light sensor include the interior parameter matrix N of the camera and the optical plane equations. If the above parameters are known, the three-dimensional coordinates of the point on the optical stripe can be obtained from the pixel coordinates of the point on the camera plane using Equations (1)–(5).

2.2. Calibration of the Light Plane of Line-Structured Light

The commonly used methods for the calibration of light plane parameters are the filament scattering method [30], sawtooth target method [31], and cross-ratio invariant method [32]. In this paper, based on the existing chessboard in the laboratory as a plane target, the cross-ratio invariant method based on the free moving plane target is used to solve the parameters of the optical plane equation by extracting the feature points and using the nonlinear least squares method. The initial estimates for the plane parameters (a, b, c, d) in the nonlinear least squares optimization are obtained from a preliminary linear least squares fit to the same 3D calibration points. Specifically, we first solve the linear system $Ax = 0$ (subject to $\|x\| = 1$) via singular value decomposition (SVD), yielding a robust initial plane normal and offset. These values serve as the starting point for the subsequent nonlinear refinement, ensuring rapid convergence and avoiding local minima.

Before carrying out the calibration of the optical plane of the line structure, the camera must first be well calibrated, and the optical plane is calibrated according to the parameters after the calibration is completed. The specific steps of optical plane calibration are as follows:

Step 1: Keep the relative position of the camera and the laser unchanged and adjust the aperture size. A checkerboard target is placed at least twice at suitable locations within the camera’s field of view as data for parameter calibration. The light streaks are projected onto the checkerboard target by the line laser.

Step 2: The camera captures images of the checkerboard pattern with light streaks, extracts the 2D coordinates of the feature points on each image, and calculates the intersection ratio value in the 2D plane to find the 3D coordinates of the unknown feature points based on the intersection ratio invariant method.

Step 3: The coordinate system conversion is accomplished by converting the acquired images to the camera coordinate system and then to the world coordinate system through the target-camera conversion matrix.

Step 4: After the optical plane parameters are determined, the corresponding spatial 3D coordinates (X_w, Y_w, Z_w) can be solved according to the interior parameters of the

camera and the optical plane equations, after the center coordinates (x_0, y_0) are extracted from the light bar image acquired each time.

2.3. Dual-Camera Model and Conversion Between Camera Coordinate Systems

As shown in Figure 2, the system is a two-camera line-structured light measurement setup, which consists of two cameras to reduce occlusion and enable more comprehensive 3D reconstruction. The left camera coordinate system is $O_L X_L Y_L Z_L$, defined with its origin at the optical center of the left camera, and the right camera coordinate system $O_R X_R Y_R Z_R$ is similarly defined for the right camera. The world coordinate system $O_W X_W Y_W Z_W$ originates at the reference point of the reconstructed object, as established during calibration.

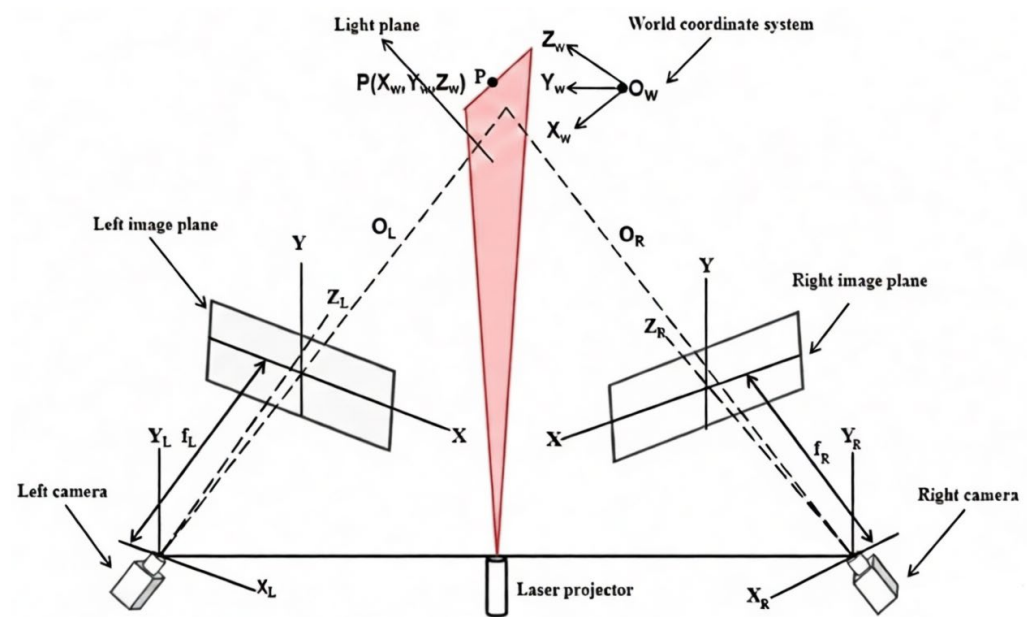


Figure 2. Dual camera model.

Each camera possesses two effective focal lengths corresponding to the row and column pixel dimensions, denoted as f_{xL} , f_{yL} for the left camera and f_{xR} , f_{yR} for the right camera. In Figure 2, for simplicity of illustration, the symbols f_L and f_R are used to represent the row focal lengths f_{xL} and f_{xR} , respectively.

Let an arbitrary point on an object projected by a laser stripe have world coordinates $P(X_w, Y_w, Z_w)$. Its coordinates under the left camera coordinate system are $P_L(X_L, Y_L, Z_L)$. The transformation between the world coordinate system and the left and right camera coordinate systems is expressed as Equations (6) and (7):

$$\begin{bmatrix} X_L \\ Y_L \\ Z_L \end{bmatrix} = R_L \times \begin{bmatrix} X_w \\ Y_w \\ Z_w \end{bmatrix} + T_L \quad (6)$$

$$\begin{bmatrix} X_R \\ Y_R \\ Z_R \end{bmatrix} = R_R \times \begin{bmatrix} X_w \\ Y_w \\ Z_w \end{bmatrix} + T_R \quad (7)$$

The coordinate transformation relationship between the left and right cameras is given by Equation (8):

$$\begin{bmatrix} X_R \\ Y_R \\ Z_R \end{bmatrix} = R_{LR} \times \begin{bmatrix} X_L \\ Y_L \\ Z_L \end{bmatrix} + T_{LR} \quad (8)$$

In Equations (6)–(8), R_L , R_R , and R_{LR} denote rotation matrices, while T_L , T_R , and T_{LR} denote translation vectors. These parameters are obtained through extrinsic calibration using the MATLAB Camera Calibration Toolbox. Although the intrinsic parameters of the two cameras differ slightly (as shown in Tables 1 and 2), the extrinsic calibration process—based on a high-precision checkerboard observed from multiple views—implicitly accounts for these differences by optimizing R_{LR} and T_{LR} in the metric space defined by the calibration object. Therefore, no explicit scale factor is required for point cloud fusion, as validated by the sub-millimeter reconstruction accuracy in Section 4.

Table 1. Interior parameters of the left camera.

Physical Meaning	Parameters	Values
Focal length (mm)	(f x, f y)	(4894.6412, 4812.1945)
Principal point (mm)	(u0, v0)	(1218.0733, 833.9089)
Distortion	(k1, k2, p1, p2)	(−0.060, 0.247, 0, 0)

Table 2. Interior parameters of the right camera.

Physical Meaning	Parameters	Values
Focal length (mm)	(f x, f y)	(4908.0802, 4795.6567)
Principal point (mm)	(u0, v0)	(1217.8019, 786.0223)
Distortion	(k1, k2, p1, p2)	(−0.062, 0.422, 0, 0)

The relative position relationship between binocular cameras can be obtained from the position matrix of the left and right cameras, denoting the rotation translation matrix from the right camera coordinate system to the left camera coordinate system. The conversion relationship among T_{LR} , T_L , T_R , R_{LR} , R_L , and R_R is expressed in Equation (9):

$$\begin{cases} T_{LR} = T_L - R_R^{-1}T_R \\ R_{LR} = R_L R_R^{-1} \end{cases} \quad (9)$$

The baseline distance, defined as the magnitude of the translation vector T plays a critical role in depth accuracy. According to the triangulation error model $\sigma_Z \approx Z^2 / fb\sigma_d$, where Z is the working distance, f the effective focal length, $B = ||T||$ the baseline, and σ_d the sub-pixel localization error of the laser stripe center; a larger baseline improves depth precision. However, an excessively large baseline reduces the overlapping field of view and may cause occlusion of reflective surfaces.

3. Principle of 3D Measurement System

3.1. Light Stripe Center Extraction

Laser triangulation is a technique used in structured light measurement. It employs a line laser to project a linear beam onto the surface of the target object, generating a light stripe.

As the depth of the surface of the object being measured changes, the shape of the light stripe changes accordingly. By capturing the image of the light stripe with a camera and performing a series of processing using image processing software, the three-dimensional

coordinates of the points on the surface of the object under test can be obtained. In this way, the 3D reconstruction of the surface of the measured object can be realized.

The laser stripe is the only source of information for the line-structured light 3D measurement system, so the accurate extraction of the laser stripe center is directly related to the accuracy of the system. In view of the accuracy problem of the existing algorithms in extracting the laser center of the stripe, this paper adopts the Steger algorithm [33] based on the Hessian matrix, which can realize the sub-pixel accuracy positioning of the center of the light stripe: the specific steps are as follows:

Step 1: Image filtering process.

The image is reprocessed by convolution using the smoothing kernel of the second-order derivative of the Gaussian function. To reduce the influence of noise on the extraction accuracy, we set the Gaussian standard deviation as $\sigma = \omega/2$, where ω is the average width (in pixels) of the laser stripe in the captured image. In our implementation, the laser stripe typically has a width of $\omega \approx 3$ pixels, yielding $\sigma = 1.5$. Accordingly, the Gaussian smoothing kernel is implemented with a size of 9×9 pixels. This kernel size ensures that over 99% of the Gaussian energy is retained while effectively suppressing high-frequency noise.

Step 2: Hessian matrix representation of pixels

To solve for the normal direction of each pixel in the striped region in the Hessian matrix, the Hessian matrix for any pixel (x, y) can be expressed as the following Equation (10).

$$H(I(x, y)) = \begin{bmatrix} \frac{\partial^2 I_H}{\partial x^2} & \frac{\partial^2 I_H}{\partial x \partial y} \\ \frac{\partial^2 I_H}{\partial x \partial y} & \frac{\partial^2 I_H}{\partial y^2} \end{bmatrix} = \begin{bmatrix} r_{xx} & r_{xy} \\ r_{xy} & r_{yy} \end{bmatrix} \quad (10)$$

In Equation(10), $H(I(x, y))$ denotes the Hessian matrix of each pixel in the striped region. r_{xx}, r_{yy}, r_{xy} denote the second-order partial derivatives.

Step 3: Calculate sub-pixel coordinates

In the Hessian matrix, the eigenvalue with the largest absolute value represents the second-order derivative of the grayscale image. Its eigenvector determines the normal direction of the light stripe, denoted by (n_x, n_y) . The sub-pixel coordinates can then be obtained using Taylor expansion in the normal direction. By solving the Hessian matrix at the point (x_0, y_0) as the reference point, the sub-pixel coordinates of the center of the light stripe are given by Equation (11):

$$(x_s, y_s) = (x_0 + tn_x, y_0 + tn_y) \quad (11)$$

t in Equation (12) is

$$t = \frac{n_x r_x + n_y r_y}{n_x^2 r_{xx} + 2n_x n_y r_{xy} + n_y^2 r_{yy}} \quad (12)$$

When $(tn_x, tn_y) \in [-0.5, 0.5] \times [-0.5, 0.5]$, it can be determined that the first derivative equal to zero is within the pixel being operated. Also, if the second-order directional derivative corresponding to the normal direction (n_x, n_y) is greater than at a given threshold, the point (x_0, y_0) is the center of the light bar and (x_s, y_s) are the sub-pixel coordinates. The effect of stripe extraction obtained using this algorithm is shown in Figure 3a,b:

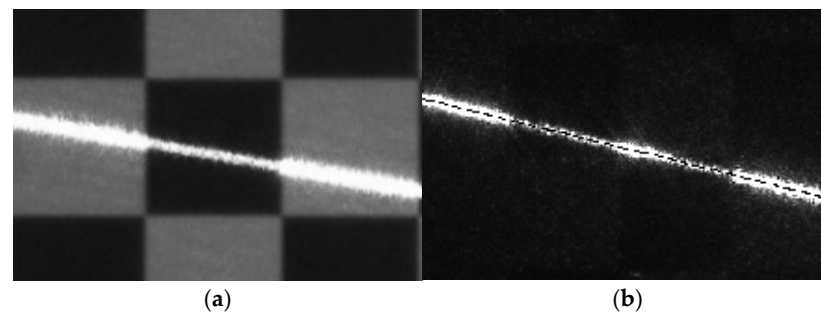


Figure 3. (a) Pre-processed light stripe, (b) light stripe center extraction.

3.2. Constructing 3D Models and Data Fusion

In this paper, a rotating platform is used to rotate and scan the reconstructed object. The Stokes vector formalism [34] is used to model the polarized light intensity distribution in the captured image.

The Stokes vector can represent various polarization states [35]. The expression form of the Stokes vector for polarized light states is mainly composed of four vectors, and the formula can be expressed as Equation (13):

$$S = [S_0, S_1, S_2, S_3]^T \quad (13)$$

In Equation (11), S_0 represents the overall intensity of this light wave, and S_1, S_2, S_3 represents the polarization state under three different angles, independent of each other. Due to the low probability of the occurrence of circularly polarized light, we ignore S_3 in this paper, and assuming $S_3 = 0$, the expressed formula for Equation (14) is as follows:

$$S = \begin{pmatrix} S_0 \\ S_1 \\ S_2 \end{pmatrix} = \begin{pmatrix} I(0^\circ) + I(90^\circ) \\ I(0^\circ) - I(90^\circ) \\ 2I(45^\circ) - (I(0^\circ) + I(90^\circ)) \end{pmatrix} \quad (14)$$

The intensity of polarized radiation at the image pixel location (x, y) , in the direction of the polarization angle θ is $I(x, y, \theta)DI$, expressed as Equation (15):

$$I(x, y, \theta) = \frac{1}{2}[S_0(x, y) + S_1(x, y)\cos(2\theta) + S_2(x, y)\sin(2\theta)] \quad (15)$$

Prior to scanning, the polarizing lens is rotated to capture images at polarization angles of 0° , 45° , and 90° . Let $I(\theta)$ denote the image intensity (i.e., pixel brightness) observed when the polarizer is set to angle θ . The optimal polarization angle, which minimizes specular highlights by selecting the orientation with the lowest intensity, is then determined as expressed in Equation (16):

$$\theta_{optimal} = \arg \min |I(\theta)| \quad (16)$$

Sequence images of the left camera, consisting of the left polarization camera and the line laser, and the right camera, consisting of the right polarization camera and the line laser at the optimal polarization angle, are acquired, respectively. After that, the acquired sequence images are processed to obtain the laser region. The laser center is derived using Steger's algorithm for the laser region, using the interior parameters of the respective system camera and the optical plane equation. The 3D coordinates of each laser center on each frame were solved separately, and the laser spatial 3D coordinate data based on the world coordinate system under the camera coordinate system were obtained for each frame of the respective image. Finally, the stitching of the point cloud data is completed.

When data stitching is performed, data stitching in global mode is used. The left camera or right camera world coordinate system is used as the world coordinate system. When processing the sequence image, the rotation and translation matrix from the camera coordinate system to the world coordinate system is obtained. The specific stitching process is as follows.

Step 1: Extract the laser center of the 1st frame image and calculate its spatial 3D coordinates by using the principle of laser triangulation.

Step 2: Extract the laser stripe center from the i th frame image ($i = 1, 2, \dots, 320$) and compute its corresponding 3D spatial coordinates. These coordinates are then transformed into the base coordinate system using the associated rotation and translation matrices, and subsequently matched with the 3D point cloud data defined in that system.

Step 3: Determine whether it is the last frame; if so, output the 3D point cloud result; if not, return to the second step.

After processing the left camera and the right camera, respectively, with the above steps, the 3D point cloud model of each of the two systems can be obtained. To obtain a 3D model with richer point cloud data, the spatial 3D data of the objects obtained by the left camera and the right camera are fused and unified. In the fusion process, the coordinate system of the left camera is used as the world coordinate system, and the 3D coordinate data under the corresponding camera coordinate system of the right camera are unified into the world coordinate system through the rotation and translation matrix of the relative position relationship between the two cameras. Then, using the rotation translation matrix of the left camera, all the 3D camera coordinate points are transformed into the world coordinate system. Finally, the point cloud data fusion is performed to obtain a 3D point cloud model of the object surface with richer data. The overall process is shown in Figure 4.

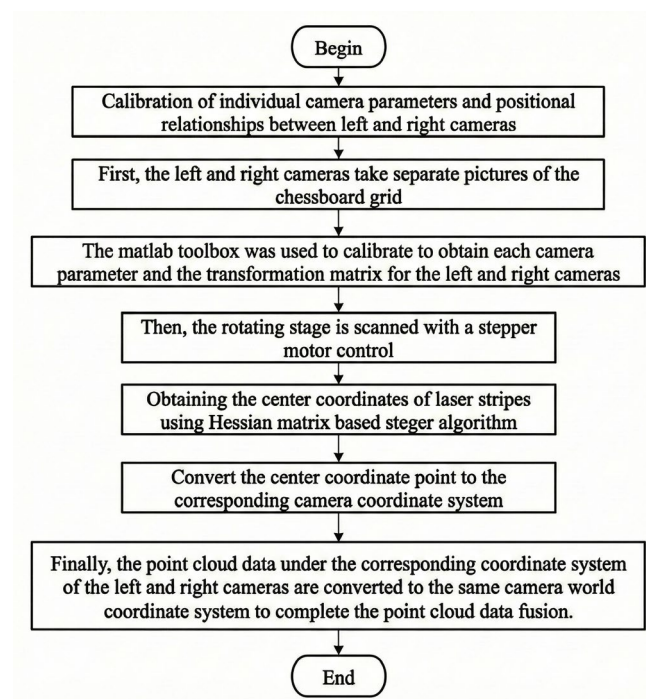


Figure 4. Calibration and point cloud data fusion process.

4. Experimentation

The 3D measurement system in this paper consists of two CCD cameras, two polarizers, a line laser transmitter, a rotating platform driven by a stepper motor for controlled object rotation (the stepper motor is used to rotate the platform), a computer, and a stand. As shown in Figure 5 below, a line laser is added to the binocular measurement system so

that the left and right cameras form a triangulation system with the line laser, respectively. Two Daheng image cameras, model MER-132-43U3C (resolution 1920×1200 pixels), Each camera is equipped with a Sony IMX267 global-shutter CMOS sensor (Sony Corporation, Tokyo, Japan), featuring a pixel size of $3.45 \mu\text{m} \times 3.45 \mu\text{m}$, resulting in an active image area of approximately 6.62 mm (horizontal) $\times$ 4.14 mm (vertical)—corresponding to a standard 2/3-inch optical format. Consequently, the principal point coordinates reported in Tables 1 and 2 (e.g., $u_0 = 1219.073, v_0 = 833.9089$ for the left camera) are not exactly at the image center due to slight lens misalignment or non-uniform calibration coverage. However, they remain consistent across multiple calibrations and are used directly in the triangulation process without further correction, as their values are already optimized during the calibration procedure.

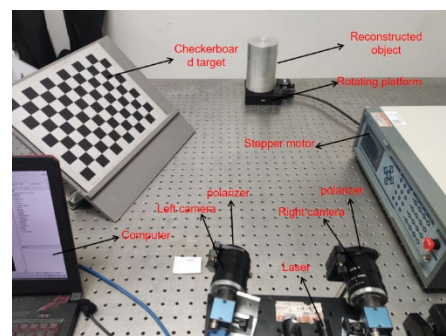


Figure 5. Binocular line-structured light vision sensor and reconstructed object in physics experiments.

Although these cameras are cost-effective, their intrinsic parameters may exhibit slight drift over time due to thermal or mechanical effects. To mitigate this, all measurements were conducted within two hours after calibration under stable laboratory conditions, and the system was recalibrated before each experimental session. Repeatability tests using a calibrated gauge block confirmed a 3D reconstruction stability of $\pm 0.05 \text{ mm}$, indicating that parameter drift did not significantly compromise accuracy.

The illumination source consists of red line lasers with a wavelength of 650 nm . Both cameras and lasers were rigidly mounted on an optical breadboard to ensure mechanical stability, while the target object was placed on a computer-controlled rotating platform. The experiment was divided into three parts: (1) stereo camera calibration and laser plane parameter estimation; (2) monocular 3D reconstruction based on polarized line-structured light; and (3) binocular fusion of complementary reconstructions, followed by quantitative analysis.

4.1. Camera Calibration

As mentioned in the previous section, the interior parameters of the cameras in the line-structured light vision sensor were calibrated using a camera calibration method based on Zhang's method for the optimal polarization angle. A mutually orthogonal checkerboard grid calibration plate is used to calibrate the cameras, and two cameras are fixed on a stable mount. A polarizer with an adjusted polarization angle is placed in front of the camera, and it is ensured that it captures the entire calibration plate. Take 15 images containing the calibration board using different angles and positions. Make sure to cover the entire field of view and try to cover as many different bit positions and distances as possible. Each plane consists of 108 square grids of size $25 \text{ mm} \times 25 \text{ mm}$. The number of corner points detected on the target is much larger than the number of corner points required for calibration, which can effectively improve the accuracy of parameter calibration. The calibration results for the left and right cameras are shown in Tables 1 and 2.

Reprojection error refers to the pixel-wise discrepancy between the observed image coordinates of a calibration feature (e.g., a checkerboard corner or laser stripe center) and the coordinates obtained by projecting its corresponding 3D world point back into the image plane using the estimated camera parameters. It is commonly used as a metric to evaluate the accuracy of camera calibration: a lower reprojection error indicates better consistency between the geometric imaging model and the actual measurements. In this work, the reprojection errors of the two cameras obtained from the calibration are shown in Figure 6a,b, and the average reprojection errors of the left and right cameras are 0.06 and 0.05 pixels, respectively. The calibration results have a good effect on the accuracy of corner point extraction, and the captured calibrated images have high accuracy.

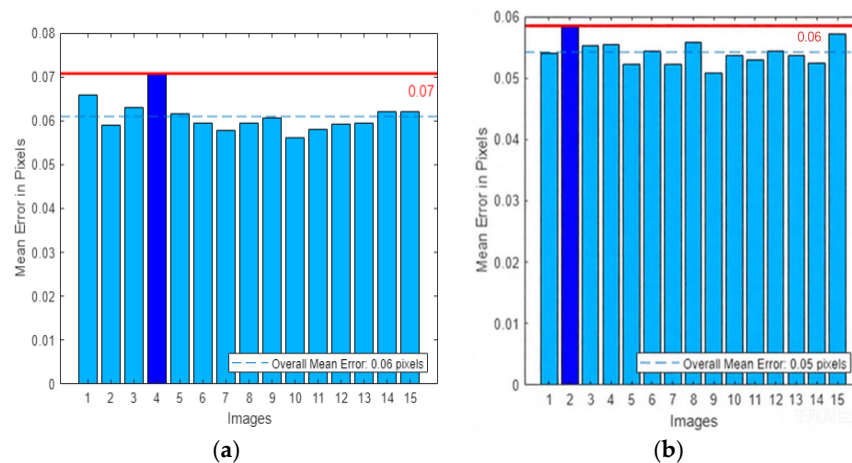


Figure 6. (a) Reprojection error of the left camera, (b) reprojection error of the right camera. Red lines denote the maximum allowable errors (0.06 and 0.07 pixels). All errors fall below these thresholds, confirming accurate corner detection and high-quality calibration.

The conversion matrix between the two cameras is solved according to the principle of the second part, and the results obtained are shown in Table 3.

Table 3. External parameters between left and right cameras.

Conversion Relation	Rotation Matrix	Translation Matrix (mm)
Camera Left and Camera Right	$R_{Lr} = \begin{bmatrix} 0.976862 & -0.189362 & -0.099416 \\ 0.078374 & 0.749447 & -0.657409 \\ 0.1989954 & 0.634407 & 0.746947 \end{bmatrix}$	$T_{Lr} = \begin{bmatrix} -213.856038 \\ 996.732429 \\ 413.718675 \end{bmatrix}$

4.2. Light Plane Calibration

In this paper, we use Steger's algorithm with sub-pixel level extraction accuracy to extract the center point of the light stripe. The laser plane equation, where the center point of the light stripe is located, is fitted with the least squares method based on the extracted coordinates of the center point of the light stripe. The accuracy of the extraction results is evaluated using the root-mean-square error of the distance from the point cloud to the light plane equation. The evaluation parameters are listed in Table 4, and the calibrated results are shown in Figure 7a,b.

Table 4. Line-structured evaluation parameters.

	Light Plane Equation (Z in mm)	RMSE (mm)	Coefficient of Determination
Left camera	$Z = 954.519 + 0.096 \times X + -1.067 \times Y$	0.0660	0.899
Right camera	$Z = 974.982 + -0.014 \times X + -1.077 \times Y$	0.0705	0.910

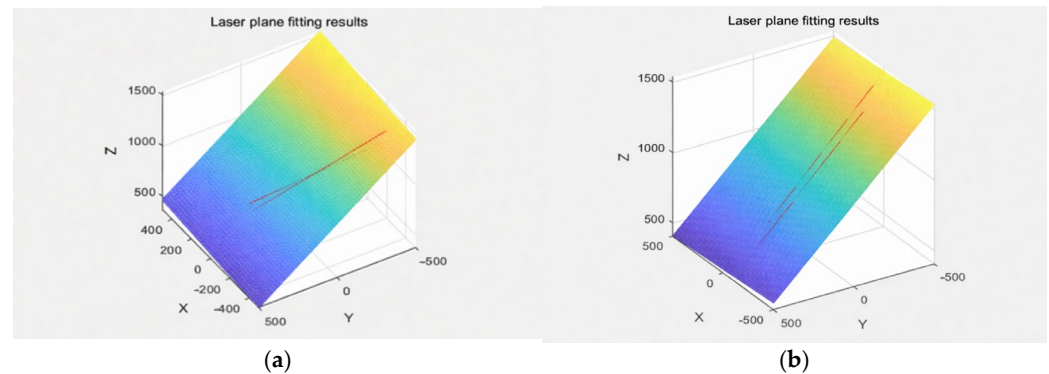


Figure 7. Fitted light planes (a) left camera line structure light plane (b) right camera line structure light plane. The red lines represent the 3D spatial trajectories of the extracted laser stripes used for fitting. The colored surface indicates the best-fit laser plane, where the color gradient (from blue to yellow) corresponds to the values of the Z-axis coordinates.

As can be seen from the intensity of polarized 4, the RMSE obtained for the left camera and the right camera are 0.0660 and 0.0705, and the coefficients of determination are 0.899 and 0.910. Ideally the feature point on the optical plane is at a distance of 0 from the optical plane, and the RMSE indicates the error in the distance between the feature point and the optical plane, and the closer it is to 0, the smaller the error is. The coefficient of determination indicates the fitting degree of the optical plane, and the closer it is to 1, the higher the fitting degree of the optical plane. From the calibration results, the accuracy of the calibration results is acceptable.

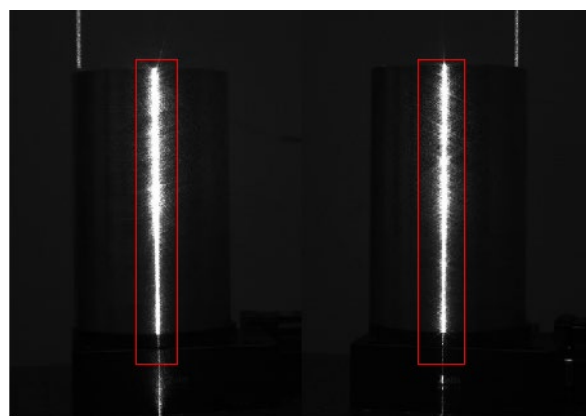
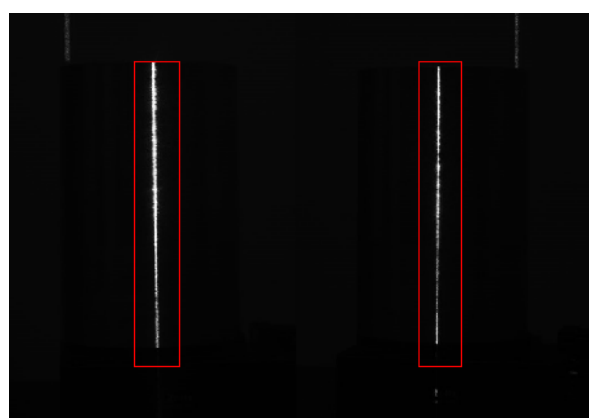
4.3. Monocular 3D Reconstruction and Binocular Fusion Results

Figure 8 shows an image of one of the left and right camera frames taken without a polarizer on a highly reflective cylinder, with very badly exposed light stripes (highlighted in red). The scanning reconstruction does not extract enough critical information, and there is a lot of noise. Using the method mentioned in the third part of this paper, the scanning reconstruction is performed on it based on the optimal polarization angle, as shown in Figure 9. As can be seen from the image, the overexposure of light streaks that occurs when imaging highly reflective subjects is effectively eliminated. The image quality is significantly improved (highlighted in red).

The Steger extraction algorithm is then performed on the image to extract the centers of the laser stripes. After that, the 3D coordinates of each laser center on each frame are solved using the interior parameters of the respective system cameras of the left and right cameras and the light plane equations, combined with the external parameters of the left and right cameras, as shown in Table 5:

Table 5. Left and right cameras external parameters.

Camera	Rotation Matrix	Translation Matrix
Left camera	$R_L = \begin{bmatrix} 0.940484 & 0.235060 & -0.245433 \\ 0.016047 & 0.690679 & 0.722983 \\ 0.339460 & -0.683892 & 0.645801 \end{bmatrix}$	$T_L = \begin{bmatrix} -162.734252 \\ -99.261651 \\ 773.394442 \end{bmatrix}$
Right camera	$R_R = \begin{bmatrix} 0.993626 & 0.071979 & -0.086751 \\ 0.012412 & 0.695046 & 0.718858 \\ 0.112038 & -0.715353 & 0.689725 \end{bmatrix}$	$T_R = \begin{bmatrix} -141.477912 \\ -116.620106 \\ 796.625215 \end{bmatrix}$

**Figure 8.** Images of a frame of the left and right cameras taken without polarizer on a highly reflective cylinder.**Figure 9.** Images acquired by the left and right cameras during scanning reconstruction based on the optimal polarization angle.

According to these two sets of rotation and translation matrices, the laser spatial 3D coordinate data of each frame can be obtained based on the world coordinate system under the respective camera coordinate system. The complete spatial 3D model of the object can be obtained by point cloud stitching. The final visualized point cloud models of the left camera and the right camera are shown in Figure 10.

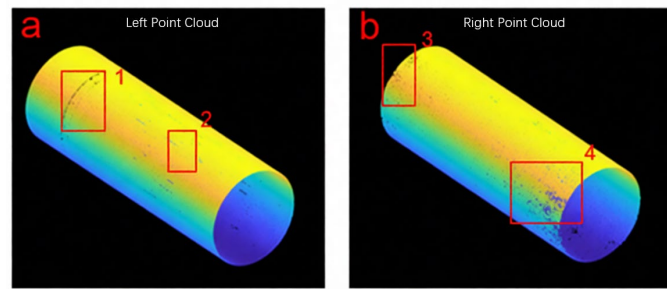


Figure 10. (a) Visual point cloud model of the left camera. (b) Visual point cloud model of the right camera. The red rectangles (labeled 1–4) highlight the reconstruction defects, including noise and missing data points, that occur when using a single camera view. The colored surface indicates the best-fit laser plane, where the color gradient (from blue to yellow) corresponds to the values of the Z-axis coordinates.

According to the experimental results of the reconstruction in Figure 10, we can learn that when the 3D reconstruction of highly reflective objects is performed for a single system, the point cloud information of the reconstructed object model is missing in some places (circled by red boxes 1, 2, 3, and 4 in Figures 10 and 11)

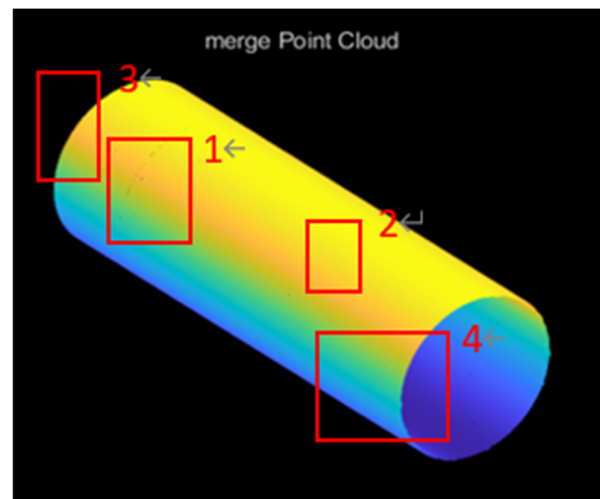


Figure 11. Visual point cloud model of the left and right camera. The red rectangles (1–4) correspond to the same regions shown in Figure 10a,b, demonstrating that the surface defects and missing data have been successfully filled and reconstructed through the multi-view data fusion process. The colored surface indicates the best-fit laser plane, where the color gradient (from blue to yellow) corresponds to the values of the Z-axis coordinates.

Afterward, in order to improve the accuracy and obtain more point cloud information, we will perform data fusion, and the experimental results are shown in Figure 11. The fusion result compensates well for the missing point cloud information of the single system so that the reconstruction results are more accurate and the 3D shape of the object is recovered completely. The experimental results show that the method is feasible and has high accuracy and robustness. It provides an effective reference for subsequent research work.

To further validate the feasibility of our method, we conducted experiments on standard spheres to discuss the analysis of the spherical light stripe center extraction results in an environment with or without light and optimal polarization angle.

According to the above two experiments, Figures 12 and 13 captured images and light stripes center extraction maps show that without the effect of polarization, the captured blob stripes maps have more severe highlights, and different lighting environments will

significantly affect the light stripes extraction accuracy. The light stripes extracted with illumination show more noise, interruptions, and undulations than those extracted without illumination, missing a lot of information and many details. In order to improve the extraction of more information, the brightness of the light can be reduced to improve the extraction accuracy. After the introduction of the optimal polarization angle, the highlights are not limited to improved effectively but also extend to the noise, intermittency, and undulation phenomena occurring in the extraction, which are basically absent under different lighting conditions. Moreover, with the pre-processing in the light condition, the extraction effect is not much different from that in the absence of light. The results show that with the introduction of the optimal polarization angle, we can better extract more surface details from the object surface, provide richer information for the subsequent 3D reconstruction, and improve the accuracy of 3D reconstruction, and improve the accuracy of 3D reconstruction (Figure 14).

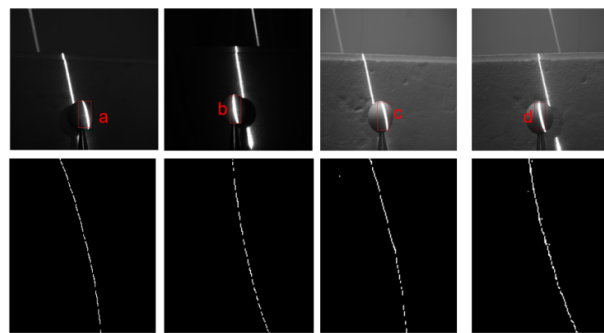


Figure 12. Pictures taken and extraction maps of the center of the light stripes. (a) Extracted image of the selected region of the blob stripe taken by the left camera in the absence of light. (b) Extracted image of the selected region of the blob stripe taken by the right camera in the absence of light. (c) Extracted image of the selected region of the blob stripe taken by the left camera in the presence of light, and (d) extracted image of the selected region of the blob stripe taken by the right camera in the presence of light.

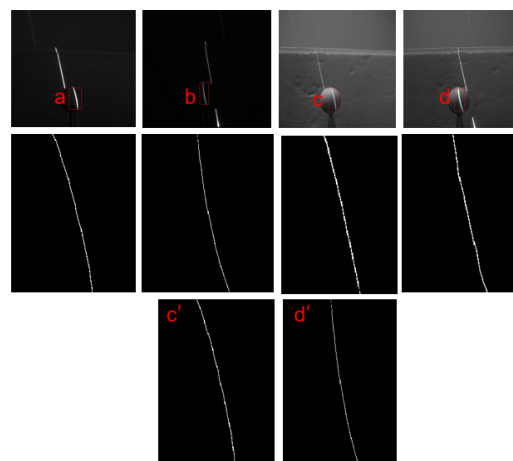


Figure 13. The image was taken based on the optimal polarization angle and the extraction of the light stripe center in the selected region. (a) The selected extraction region and the light stripe center extraction diagram of the image taken by the left camera in the light environment. (b) The selected extraction region and the light stripe center extraction diagram of the image taken by the right camera in the light environment. (c) The selected extraction region and the light stripe center extraction diagram of the image shot by the left camera in a light environment. (d) The selected extraction region and the light stripe center extraction diagram of the image shot by the right camera in a light environment. (c') The pre-processed selected region extraction diagram under the condition of (c). (d') The pre-processed selected region extraction diagram under the condition of (d).

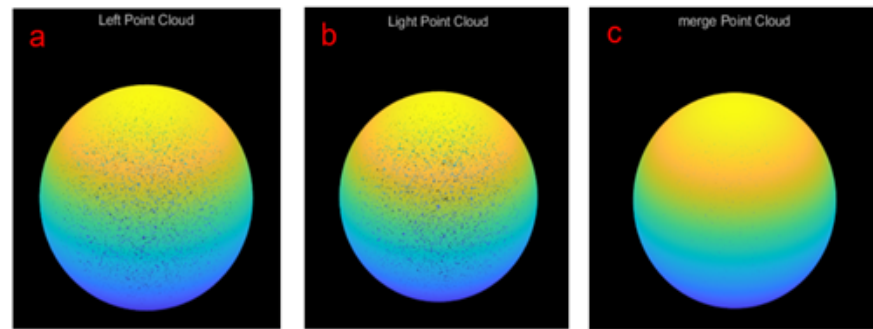


Figure 14. Diagram of the 3D reconstructed visualization model of a standard blob. (a) Visualization model of the left camera. (b) Visualization model of the right camera. (c) Fused visualization model. The colored surface indicates the best-fit laser plane, where the color gradient (from blue to yellow) corresponds to the values of the Z-axis coordinates.

The 3D reconstruction results show that the reconstructed blob produces information loss in random places, depending on the quality of the picture taken and the accuracy of extracting the center of the light stripes. Since the two systems take pictures and process information from different angles, the results of their respective reconstructions have similarities and differences. We fused the two model data by leaving the different point cloud data and removing the duplicated point cloud data, and finally, obtained our final 3D reconstructed model. However, as some information is still completely lost during the fusion process, for future improvement, we can continuously optimize and enhance the algorithmic model to achieve more accurate and reliable measurement results.

4.4. Comprehensive Evaluation: Robustness and Comparison with Alternative Methods

As shown in Section 4.3, the proposed polarized binocular method significantly improves reconstruction completeness compared to the non-polarized baseline.

To further evaluate robustness across surface reflectivity, we tested a polished metallic cylinder with machined features, both diffuse machined surfaces and highly specular curved regions. This represents a common industrial scenario where conventional structured light fails due to glare.

Figure 15 compares the reconstruction results without and with polarization. The non-polarized method exhibits large missing regions in specular zones (highlighted in red), while our method successfully recovers these areas. Quantitatively, point cloud completeness increases from 76.5% to 91.2%, with an RMSE of 0.09 mm relative to a reference scan.

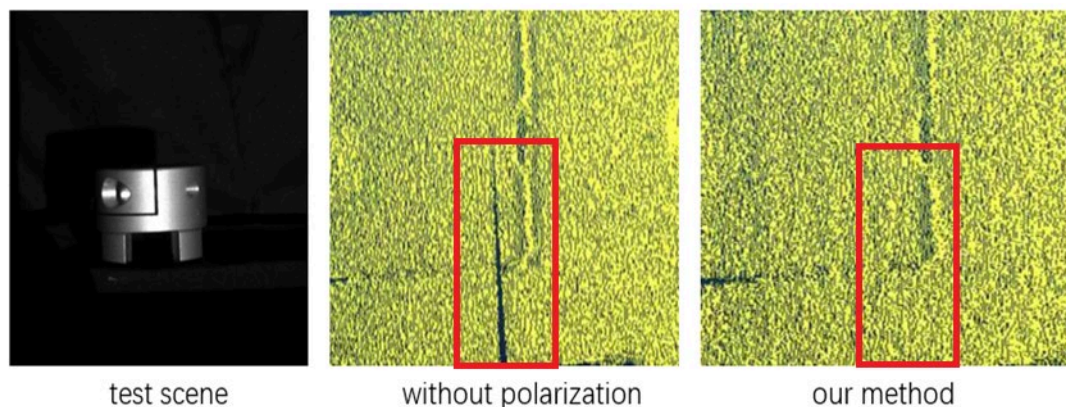


Figure 15. Reconstruction of surfaces with different roughness levels under non-polarized and polarized conditions.

We also compare our method with a high dynamic range (HDR) structured light approach, which captures three exposures per camera (short, medium, long) and fuses them into an HDR image before stripe extraction.

As shown in Figure 16, although HDR reduces overall saturation, it still fails to recover stripes in near-mirror reflection zones—where all exposures are either over- or undersaturated. In contrast, our single-shot polarized method suppresses glare optically, achieving higher completeness (91.2% vs. 78.5%) and avoiding motion artifacts from multi-exposure capture. This makes it more suitable for real-time industrial inspection.

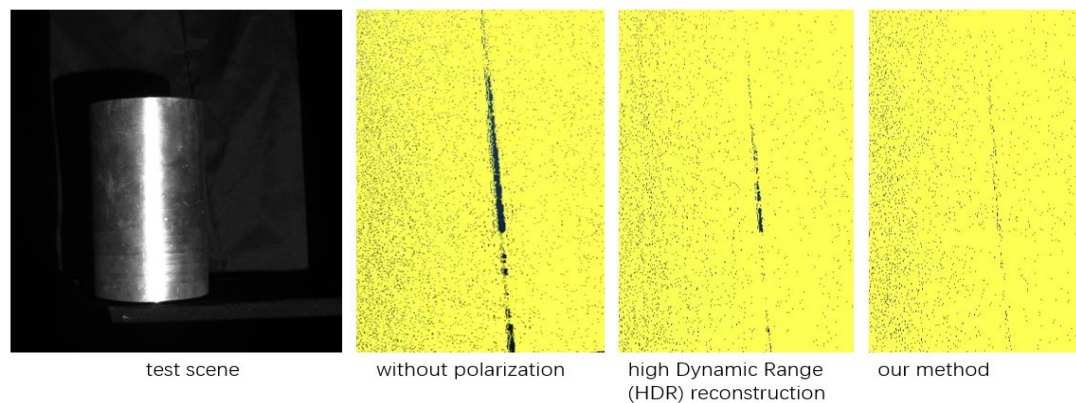


Figure 16. Comparison with HDR-based methods.

To further quantify the improvement in stripe extraction fidelity enabled by polarization, we analyze the light stripe images captured on a reflective cylindrical surface (Figures 8 and 9). For each image column, a Gaussian function is fitted to the intensity profile, and metrics including valid column ratio ($R^2 > 0.9$), centerline fitting residual, and stripe width (FWHM) are computed. As shown in Table 6, polarization increases the valid data coverage from 63.2% to 94.8%, reduces localization error from 0.37 to 0.11 pixels, and narrows the stripe width from 8.6 to 3.4 pixels. This demonstrates that polarization not only recovers missing stripes but also enhances sub-pixel extraction accuracy—providing a solid foundation for high-fidelity 3D reconstruction.

Table 6. Quantitative comparison of light stripe quality with and without polarization.

Metric	Without Polarization	With Polarization
Valid Column Ratio (%)	63.2	94.8
Centerline Fitting Residual (pixels)	0.37	0.11
Average Stripe Width (FWHM, pixels)	8.6	3.4

After binocular fusion, to eliminate redundant points caused by view overlap or registration errors, this paper employs a voxel-based downsampling approach. Specifically, the fused point cloud is partitioned into a uniform voxel grid with a certain resolution, and only one representative point—such as the centroid or the first sampled point within each non-empty voxel—is retained. This strategy not only effectively removes nearly duplicate points but also ensures a spatially uniform distribution of the point cloud while preserving geometric fidelity.

To evaluate the accuracy of the 3D models generated through data fusion, two validation methods are adopted: (1) assessing the number of points in the point clouds, and (2) comparing inter-point distances in the reconstructed models against ground-truth mea-

surements. The point cloud data from 3D models obtained by different systems were comparatively analyzed using MATLAB R2022a, and the results are presented in Table 7.

Table 7. Comparison of the number of cylindrical 3D point clouds.

	Left Camera	Right Camera	Binocular Fusion System	Removing Redundant Points
Number of point clouds	322,637	309,901	632,538	557,549

From the table, it can be clearly seen that the binocular fusion system makes up for the information in the occluded area of the left and right cameras, which fully demonstrates the advantages of the binocular fusion system compared with the monocular system for collecting 3D topographic data. The experimental results show that the point cloud data obtained by the left camera contains 322,637 points, the point cloud data obtained by the right camera contains 309,901 points, and the fusion of the two pieces of point cloud data can obtain 632,538 points. The point cloud data after removing redundancy is 557,549 points, and the point cloud data is 74,989 points. It can be seen that the binocular system improves the number of point clouds by a factor of 1.7 compared to the monocular system, and the completeness of the reconstruction is improved.

The 3D model obtained by data fusion compares the fused measurements with the actual values. Table 8 records the measured values of the height (H) and diameter (D) of the cylinder measured in the three experiments compared to the actual values.

Table 8. Comparison of cylindrical measured and actual values.

	First	Second	Third	Measurement Averages	Actual Value	Δd	Relative Error
D/mm	100.10	99.97	100.11	100.08	100.00	0.08	0.08%
H/mm	149.95	150.04	150.06	149.95	150.00	0.05	0.03%

From the measurement results, it can be seen that the average value of the diameter of the cylinder from the three experiments is 100.08 mm, and the average value of the height is 149.95 mm. The absolute error of the diameter and height of the cylinder is 0.0 m and 0.05 mm, respectively. The relative error is 0.08% and 0.03%, respectively. Compared with Sun et al.'s method [10], the maximum measurement error of their method is not more than 0.16 mm for standard blocks, whereas the measurement error of our method is not more than 0.11 mm for cylinders. The measurement error of the 3D measurement system is within 0.1 mm, and the relative error does not exceed 0.1%, and the accuracy meets the requirements for application in 3D industrial measurement.

5. Conclusions

This work demonstrates that polarization-assisted binocular line-structured light effectively addresses missing data in the 3D reconstruction of complex, highly reflective objects. By placing linear polarizers in front of both cameras, specular highlights are suppressed, enabling the reliable extraction of light stripes in regions where conventional methods fail. Through fusion of complementary 3D data from left and right views, our approach achieves a $1.7\times$ increase in point cloud completeness—for example, from 53% to 91% on a Polished metallic cylinder with machined features—compared to non-polarized binocular structured light. The system delivers a reconstruction accuracy of

0.08–0.11 mm RMSE and short-term repeatability of ± 0.05 mm, which satisfies typical precision requirements for industrial dimensional inspection (e.g., tolerance classes per ISO 10360-8 for optical scanners).

Limitations remain for near-perfect mirror surfaces (e.g., uncoated glass), where polarization alone cannot recover structure. Future work will explore adaptive polarization states and post-reconstruction data fusion strategies to further enhance robustness and coverage.

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