

Article

System Structural Error Analysis in Binocular Vision Measurement Systems

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Abstract: A binocular stereo vision measurement system is widely used in fields such as industrial inspection and marine engineering due to its high accuracy, low cost, and ease of deployment. An unreasonable structural design can lead to difficulties in image matching and inaccuracies in depth computation during subsequent processing, thereby limiting the system's performance and applicability. This paper establishes a systemic error analysis model to enable the validation of changes in structural parameters on the performance of the binocular vision measurement. Specifically, the impact of structural parameters such as baseline distance and object distance on measurement error is analyzed. Extensive experiments reveal that when the ratio of baseline length to object distance is between 1 and 1.5, and the angle between the baseline and the optical axis is between 30 and 40 degrees, the system measurement error is minimized. The experimental conclusions provide guidance for subsequent measurement system research and parameter design.

Keywords: binocular stereo vision systems; measurement error



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1. Introduction

Binocular stereo vision measurement is an efficient, non-contact measurement technology that achieves precise object measurement by determining three-dimensional coordinates. It is widely used in fields such as autonomous driving and industrial inspection [1–3]. In recent years, discussions within the field of binocular vision systems have predominantly centered on “camera calibration, feature point matching, and stereo matching” [4–6] while largely overlooking the impact of system architecture design on measurement accuracy. An unreasonable camera system layout can cause issues such as a limited field of view, shooting occlusion overlap, reduced effective field of view, and increased disparity noise. Research on the layout of binocular stereo vision systems aims to optimize the disparity range, reduce disparity noise, and minimize occlusion problems to ensure the system's reliability and stability [7]. In a binocular vision system, a reasonable system structure is arranged to complete the task of measuring the three-dimensional parameters of an object [8,9].

This paper analyzes the factors affecting the measurement accuracy of binocular systems through mathematical modeling and experimental verification. The main contributions are as follows:

1. The error analysis model for binocular stereo vision measurement systems is refined in this study by considering the relationships among object distance, baseline length, and the angle between the baseline and the optical axis. This provides a comprehensive model for analyzing the impact of system structural parameters on measurement accuracy.

2. Experimental verification and nonlinear analysis are conducted to determine the impact of baseline length and object distance variations on binocular measurement errors, suggesting an optimal range for the K value (the ratio of baseline length to object distance).
3. The impact of the angle between the optical axis and the baseline on measurement accuracy is analyzed, and the optimal range is determined to be between 30° and 40° .

The structure of this paper is as follows: Section 2 introduces recent research related to the parameters of binocular stereo vision systems. Section 3 constructs an error analysis model for binocular stereo vision and delves into the impact of system structural parameters on measurement errors. A detailed description of the experimental design, including the specific arrangement of the binocular stereo vision experimental setup, as well as the analysis of the experimental data, is illustrated in Section 4. Finally, Section 5 summarizes this paper, offering theoretical and practical suggestions to optimize measurement accuracy.

2. Related Work

This section primarily reviews research on factors that cause measurement errors in binocular stereo vision. Notably, a detailed study of binocular stereo vision measurement system layout based on modeling is introduced.

2.1. Research on System Intrinsic Parameters

Currently, the factors affecting the accuracy of binocular vision measurement mainly involve intrinsic and extrinsic system parameters. Among them, intrinsic system parameters include the effective focal length of the two cameras, the size of the field of view, and the nonlinear distortion coefficients [10,11]. The extrinsic system parameters mainly include the angle between the optical axes of the two cameras, the baseline distance (B), and the object distance [12,13]. The measurement errors caused by the differences in these system structural parameters are referred to as systematic errors [14]. Pan et al. [14] proposed a distortion coefficient estimation method based on linear least squares to eliminate measurement errors caused by camera distortion in 2D digital image technology. David et al. [15] introduced a rational function model and applied it to radial lens distortion correction in wide-angle and catadioptric lenses. Jia et al. [16] developed a camera's intrinsic parameter calibration method based on active vision and vertical compensation, eliminating the impact of non-perpendicular camera movement on calibration accuracy. Mikko et al. [17] proposed a method for evaluating binocular camera accuracy by changing focal length, validating the impact of focal length changes on measurement accuracy. Sunil et al. [18] discovered, through theoretical derivation and Monte Carlo simulation, that noise significantly affects the intrinsic parameters of the camera, especially the image center and scale factor. However, intrinsic system parameters are often fixed once the cameras and lenses are selected. Extrinsic system parameters have a greater influence and need to be considered more.

2.2. Research on System Extrinsic Parameters

Recent advancements in stereo camera systems, particularly in underwater environments, underscore the importance of accurately understanding and calibrating system extrinsic parameters. For example, Su et al.'s [19] precise 3D measurements of marine propeller deformation using stereo digital image correlation, Williams et al.'s [20] method for accurate volumetric fish density estimation incorporating seafloor adjustments and range-based detectability, and Pi et al.'s [21] stereo Visual SLAM system for autonomous underwater vehicles all demonstrate how critical these parameters are in achieving reliable results under challenging conditions.

Current research on extrinsic system parameters, such as baseline distance, object distance, and the angle between the baseline and optical axis, primarily involves deriving geometric relationships and using numerical simulations to evaluate changes in system accuracy. For instance, Xu et al. [22] concluded, through semi-physical simulations, that

intrinsic and extrinsic parameters, including baseline distance and the angle between the camera and the optical axis, determine reconstruction accuracy. Similarly, Xing et al. [23] found that camera baseline and pixel capturing accuracy directly impact camera positioning accuracy through resolution error modeling. Shiqigao et al. [24] introduced uncertainty into error analysis models, showing that measurement errors within the Fov (field of view) increase with object distance. Zhang et al. [25] created mathematical models based on structural parameters to guide system design, while Zhou et al. [26] developed an underwater refraction model for more accurate calibration. Research on the influence of external system structural parameters, such as baseline distance, on measurement accuracy has been conducted for a considerable time. David F. Llorca et al. examined the impact of baseline distance on depth error in pedestrian detection, finding that increasing baseline length effectively reduces depth estimation error at greater object distances [27]. Tao Zhang et al. analyzed depth reconstruction errors in stereo vision, proposing a noise-ray intersection model; they found an optimal finite baseline, challenging the idea that larger is better [28]. Lu Yongkang et al. found that while a longer baseline reduces depth error, it introduces other errors, requiring balanced optimization [29]. These studies provide only partial analysis and lack a comprehensive assessment of extrinsic parameter impacts on accuracy. Moreover, the experimental validations are often limited.

3. Measurement Error Analysis Model for Binocular Vision

In a traditional binocular stereo vision measurement system, as illustrated in Figure 1, under ideal conditions, two CCD cameras are placed horizontally. CCD1 and CCD2 represent the image planes of the two cameras. The coordinate systems of the left and right cameras are denoted as $O_1X_1Y_1$ and $O_2X_2Y_2$, respectively. The optical centers of the two cameras are denoted as O_1 and O_2 , and the line connecting the image plane centers o_1 and o_2 is denoted as O_1o_1 and O_2o_2 , respectively. These lines represent the optical axes of the left and right cameras. The straight line O_1O_2 represents the baseline B , which is the distance between the two cameras. A point P in space with coordinates (X, Y, Z) projects onto the image planes of the two cameras as p_1 and p_2 , with coordinates (x_1, y_1) and (x_2, y_2) , respectively [30–34]. The real angles formed by the lines O_1P and O_2P with their respective optical axes in the image plane are φ_1 and φ_2 . The horizontal projection points are denoted as P' , and the real angles formed by O_1P' and O_2P' with the optical axes are ω_1 and ω_2 . It is important to note that θ_1 and θ_2 represent the angles $\alpha_1 + \omega_1$ and $\alpha_2 + \omega_2$, respectively. The corresponding image points p_1 and p_2 on the left and right cameras have focal lengths f_1 and f_2 , respectively. We establish a world coordinate system (O, X_w, Y_w, Z_w) with the optical center of the left camera O_1 as the origin, and the Z axis as the baseline B [35–37].

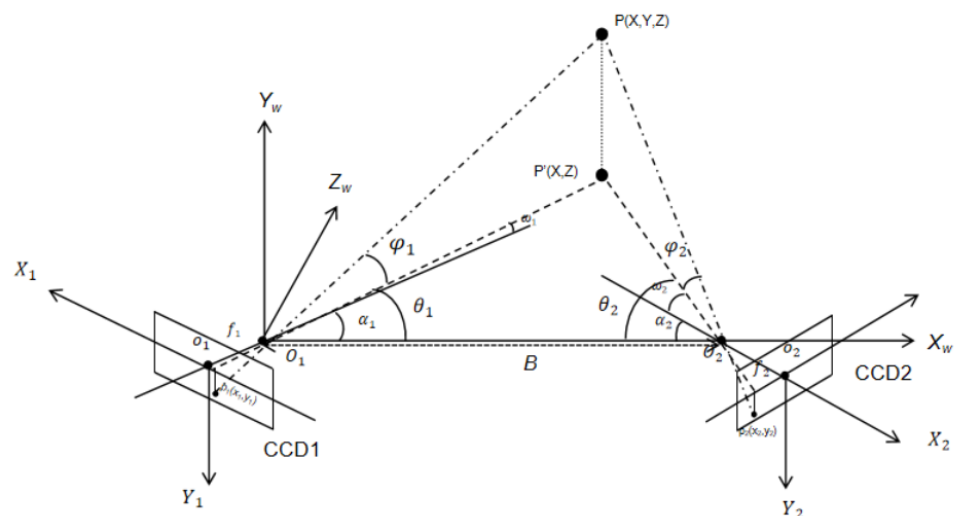


Figure 1. A structural model of a binocular vision measurement system.

From the geometric relationships depicted in Figure 1, the spatial coordinates of point P can be determined, as shown in Equation (1).

$$\begin{cases} X = \frac{B \cot \theta_1}{(\cot \theta_1 + \cot \theta_2)} \\ Y = \frac{Z}{\sin \theta_1} \cdot \frac{y_1 \cos w_1}{f_1} = \frac{Z}{\sin \theta_2} \cdot \frac{y_2 \cos w_2}{f_2} \\ Z = \frac{B}{(\cot \theta_1 + \cot \theta_2)} \end{cases} \quad (1)$$

To simplify the analysis, we assume ideal conditions with a distortion-free camera and infinite resolution. The coordinates of the spatial measurement point P can be obtained by solving a multivariable function composed of the system's structural parameters [38], as shown in Equation (2).

$$(X, Y, Z) = F(B, \alpha_1, \alpha_2, f_1, f_2, x_1, x_2, y_1, y_2) \quad (2)$$

According to the error propagation theory [39], the systematic error of the spatial point P can be expressed as a combination of errors in X, Y, Z , as shown in Equation (3).

$$\gamma = \sqrt{(\Delta X)^2 + (\Delta Y)^2 + (\Delta Z)^2} = \sqrt{\sum_i \sum_j \left(\frac{\partial F}{\partial j} \cdot \delta_j \right)^2} \quad (3)$$

where γ is the total error, including three directions X, Y, Z . i represents the direction of X, Y, Z . j is one of the parameters including $B, \alpha_1, \alpha_2, \omega_1, \omega_2, f_1, f_2, x_1, x_2, y_1$, and y_2 , and δ_j is the error coefficient.

The propagation coefficients in the X, Y, Z directions can be determined based on the structural model of the binocular system [25,39,40]. To simplify the analysis and provide a clearer visualization, a top view of the system structure is illustrated in Figure 2.

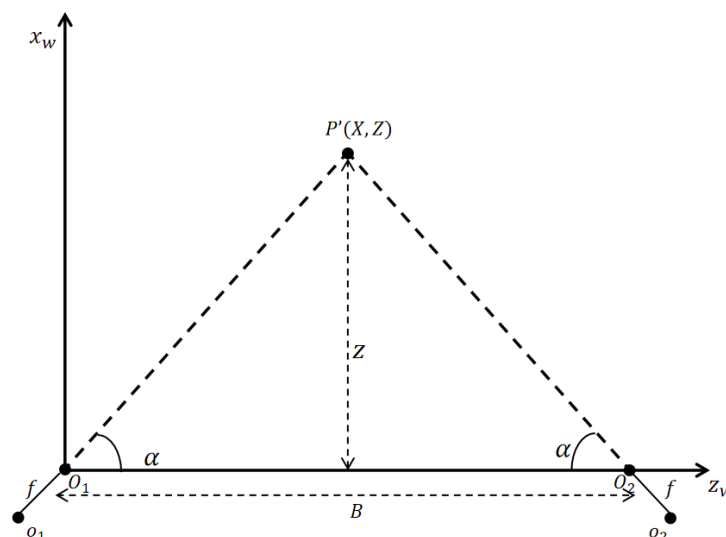


Figure 2. An overhead view of the binocular vision system architecture.

We set $\varphi_1 = \varphi_2 = 0$. At this point, the spatial point P is on the same horizontal plane as the baseline B , and therefore, the error propagation factor in the Y_w axis direction is not considered. Let $K = B/Z$, $\omega_1 = \omega_2 = 0$, $\alpha_1 = \alpha_2 = \alpha$, and $f_1 = f_2 = f$. The systematic error can then be expressed as [25]:

$$\begin{cases} \gamma = \sqrt{(\Delta X)^2 + (\Delta Z)^2} = \sqrt{e_1^2 + e_2^2} = \frac{\sqrt{2} \cdot z}{f} \cdot e_3 \\ e_1 = \frac{1}{K} \cdot \cot \alpha \cdot \sin^{-2} \alpha = \frac{1}{2} + \frac{k^2}{8}, \\ e_2 = \frac{1}{K} \cdot \sin^{-2} \alpha = \frac{1}{K} + \frac{K}{4}, \end{cases} \quad (4)$$

The systematic error curve corresponding to parameter K is illustrated in Figure 3.

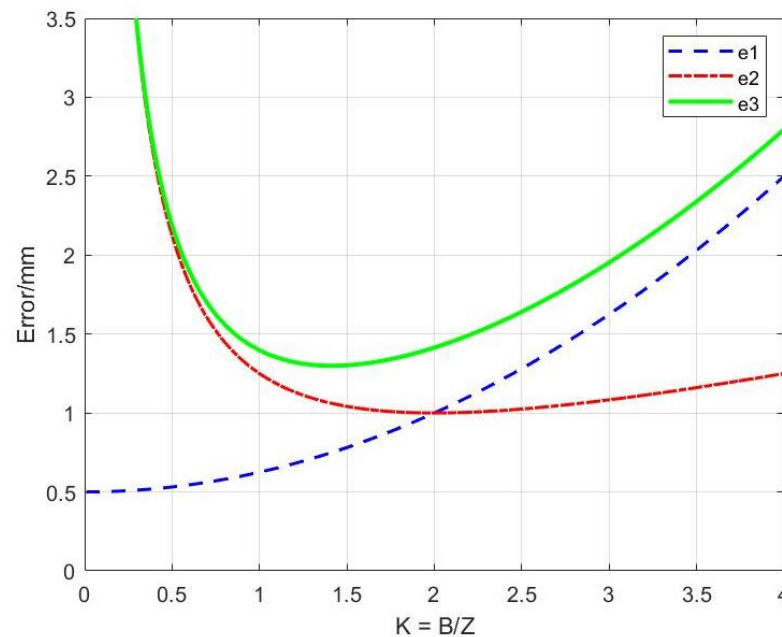


Figure 3. The distribution curve of the systematic error for parameter K .

As can be seen from Figure 3, when K varies between 0 and 1.5, the variation in the e_1 curve is relatively small, while the variation in the e_2 curve is relatively large. Combined with Equations (4) and (5), it can be seen that the impact of the object distance Z on the systematic error is greater than that of the baseline length. However, when K is greater than 1.5, the opposite is true: the variation in the e_1 curve is relatively large, and the variation in the e_2 curve is relatively small. At this point, the key factor affecting the systematic error is the baseline length. Therefore, when setting up a binocular system, it is necessary to consider the application scenario and adjust the ratio between the baseline distance B and the object distance Z in a timely manner to meet the system's accuracy requirements.

At the same time, the angle between the optical axis and the baseline α restricts the relative orientation and position of the cameras and, therefore, must also be taken into consideration. According to Equations (1) and (3), we set φ to be 45° , and the error transfer function α can be derived as [40]:

$$\gamma_{\alpha,B} = B \sqrt{\frac{(\cot^2 \alpha + 1)^2}{(2 \cot \alpha)^4} + \frac{\cot^2 \alpha (\cot^2 \alpha + 1)^2}{(2 \cot \alpha)^4} + \frac{\cot^2 \alpha}{\sin^4 \alpha (2 \cot \alpha)^2}} \quad (5)$$

where $\gamma_{\alpha,B}$ is the systematic error caused by α or B .

The variation curve of the systematic error with respect to the external parameter errors of the camera is shown in Figure 4. When the baseline distance is set to 120 mm, the systematic error variation curve of γ_α is shown in Figure 4a.

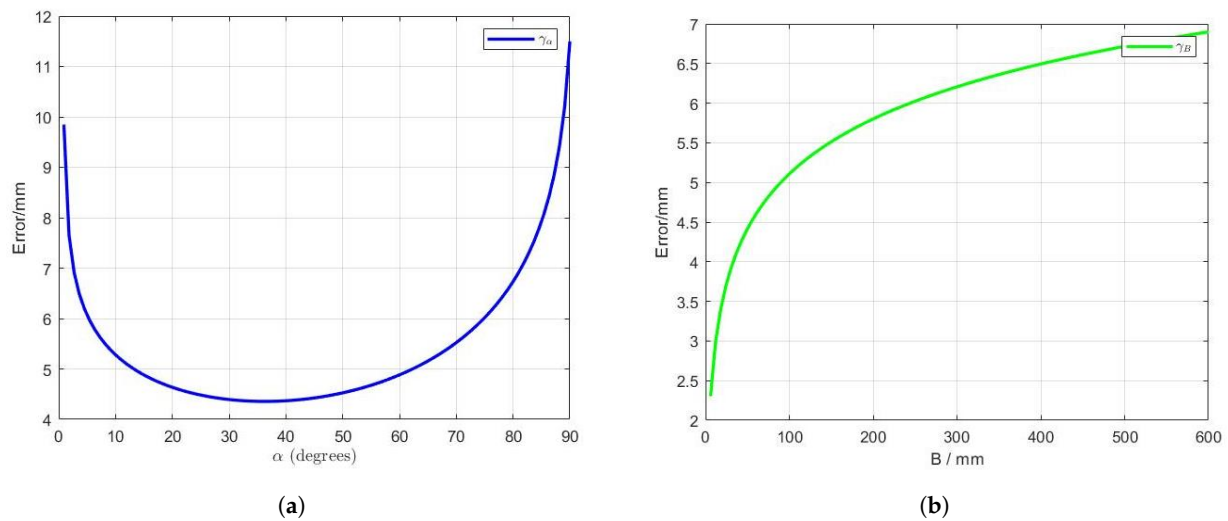


Figure 4. Variation curve of systematic error relative to external camera parameter error. (a) Distribution curve of systematic error with respect to angle between baseline and optical axis; (b) variation curve of systematic error relative to baseline length.

According to Figure 4a, as α changes from 0° to 36° , the systematic error gradually decreases. When α exceeds 36° , the systematic error gradually increases again. Therefore, when designing a binocular stereo vision measurement system, the angle between the optical axis and the baseline should be set between 30° and 40° . At this range, the systematic error is relatively small.

When the angle α is assumed to be 36° and $\varphi = 45^\circ$, the error e_1 , which represents the systematic error in the X direction in Figure 3, shows a similar trend to that in Figure 4b. An analysis of Figure 4b reveals that when the angle between the camera and the optical axis is fixed, the systematic error increases gradually with an increase in the baseline distance, though it tends to level off. Therefore, it can be inferred that as the baseline length increases, this leads to an accumulation of triangulation errors in the X direction. Combining Figure 3 with Figure 4b indicates that when k is between 0 and 1.5, the systematic error of the e_1 curve in the X direction gradually increases with the increase in baseline length. By combining Figure 4a,b, we construct an overall error surface that integrates baseline distance and object distance, as illustrated in Figure 5.

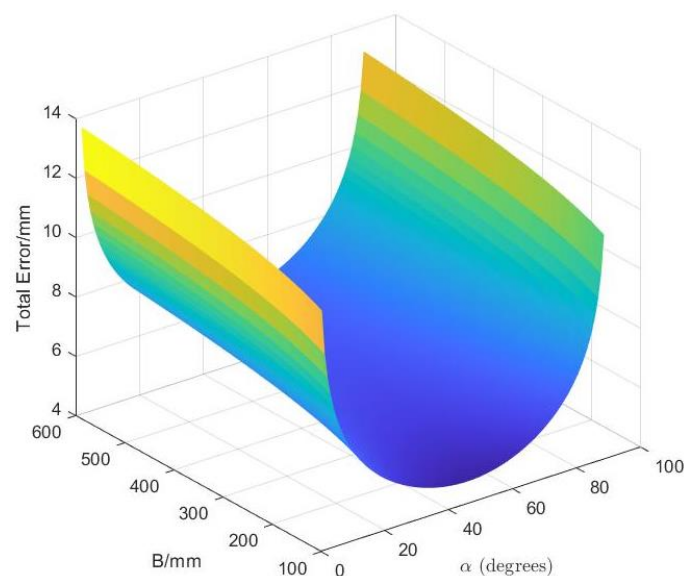


Figure 5. Total error distribution curve of system structural parameters.

By analyzing Figures 3 and 5, where different colors represent varying levels of total error (warmer colors indicating higher error and cooler colors indicating lower error) it can be inferred that when configuring a binocular vision measurement system, the angle between the baseline and the optical axis should ideally be maintained between 30° and 40° . Additionally, the K value should ideally be maintained between 1 and 1.5 to ensure the measurement accuracy of the system. This conclusion will be experimentally verified in Section 4.

4. Experiments and Results

4.1. Experiment System

The binocular measurement system setting is shown in Figure 6. In this experiment, two sets of USB cameras with a resolution of 1960×1080 , a focal length of 4 mm, and a pixel size of $3 \mu\text{m} \times 3 \mu\text{m}$ were used, along with a high-precision calibration board measuring $3600 \times 2700 \text{ mm}$ with an error of 0.001 mm. The system also included a binocular camera tripod with an adjustable height ranging from 50 cm to 150 cm, a baseline adjustable range from 20 mm to 350 mm, and a pan-tilt adjustment range from 0 to 180 degrees. The object measured was a standard 27 mm chessboard pattern.

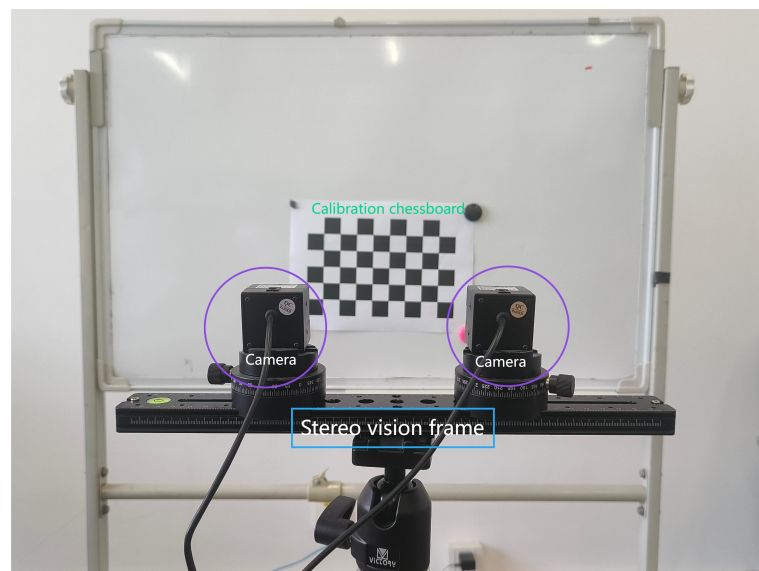


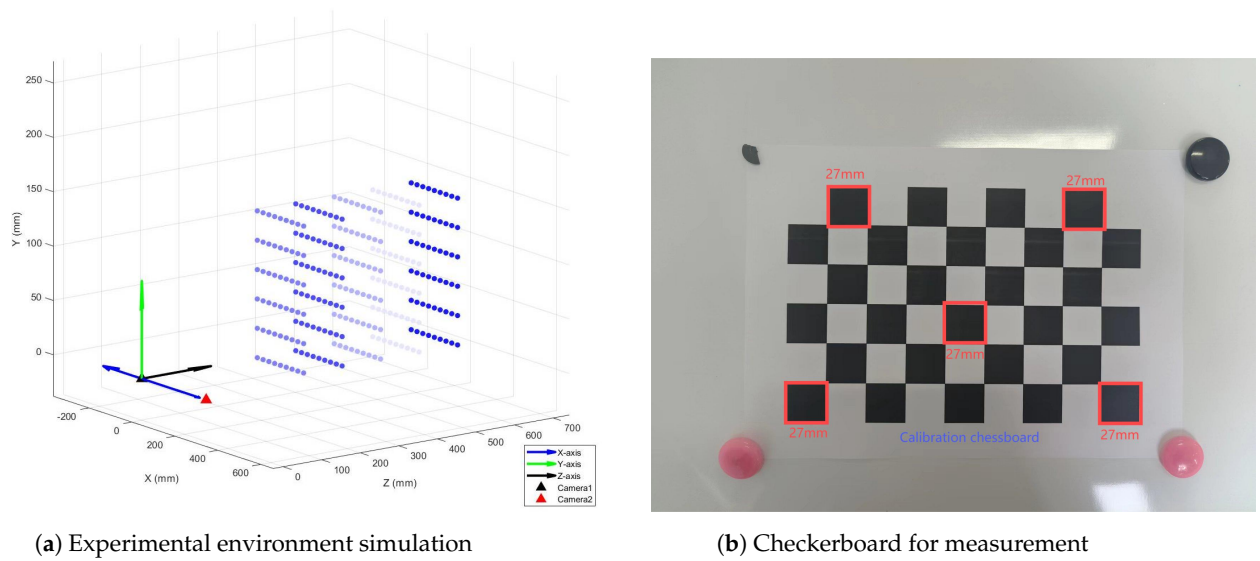
Figure 6. System structure.

4.2. Experimental Results

In this chapter, we conducted two experiments to verify the accuracy of the simulation analysed in Section 3. In both experiments, We calibrated the stereo camera with the obtained intrinsic parameters and relative rotation and translation matrices, and imported them into Python (version 3.10) for distortion correction using OpenCV (version 4.8.1). To minimize errors, we manually selected feature points for stereo matching. Experiment one was designed to verify that the factors causing measurement errors change with variations in the K value, with the optimal range for K being 1–1.5. Experiment two confirmed the conclusion that the optimal angle setting between the optical axis and the baseline in the system is 35° .

4.2.1. Experiment I

A schematic illustration of the experimental setup design is presented in Figure 7a. The measurement chessboard shown in Figure 7b was positioned at distances ranging from 300 mm to 700 mm from the camera for capturing images. The baseline length B was initially set to 50 mm and subsequently adjusted in 50 mm increments up to 250 mm. The length of a single chessboard square (27 mm) was measured in each configuration.



(a) Experimental environment simulation

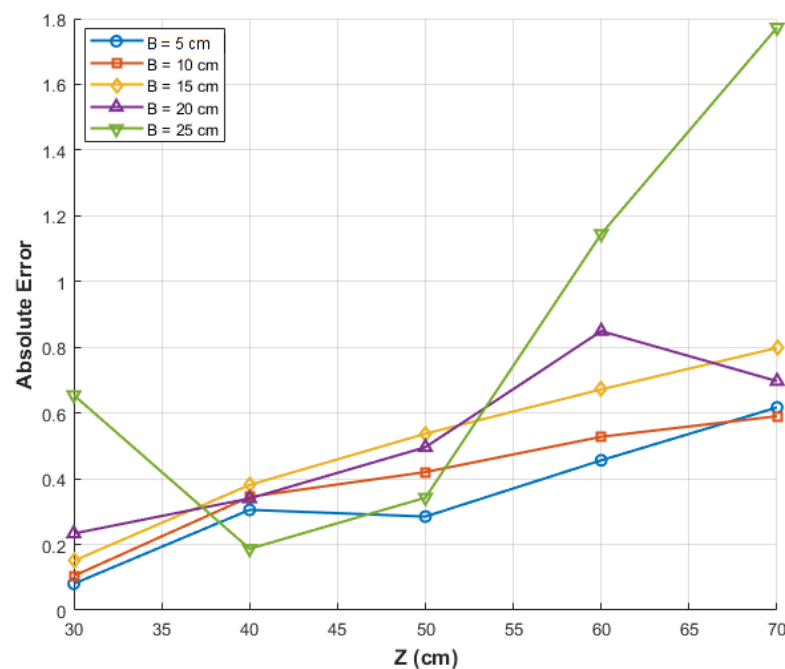
(b) Checkerboard for measurement

Figure 7. Experimental setup.

In the experiment, we utilized the intrinsic and extrinsic parameter matrices obtained from camera calibration to perform distortion correction on the captured chessboard images. To minimize noise and discontinuities during the stereo matching process, we manually selected image feature points multiple times, aiming to reduce experimental errors as much as possible. The measurement error curves are presented in Table 1 and Figures 8 and 9.

Table 1. Measurement results of target (unit: mm).

B/Z	30 cm	40 cm	50 cm	60 cm	70 cm
5 cm	26.9195 mm	27.3054 mm	26.7151 mm	26.5440 mm	26.3830 mm
10 cm	27.1043 mm	26.6551 mm	26.5797 mm	26.4722 mm	26.4097 mm
15 cm	27.1504 mm	26.6189 mm	26.4629 mm	26.3282 mm	26.2018 mm
20 cm	26.7665 mm	26.6601 mm	27.4959 mm	27.8492 mm	26.3031 mm
25 cm	27.6544 mm	26.8131 mm	26.6576 mm	25.8550 mm	28.7729 mm

**Figure 8.** Impact of Z on systematic error at different B.

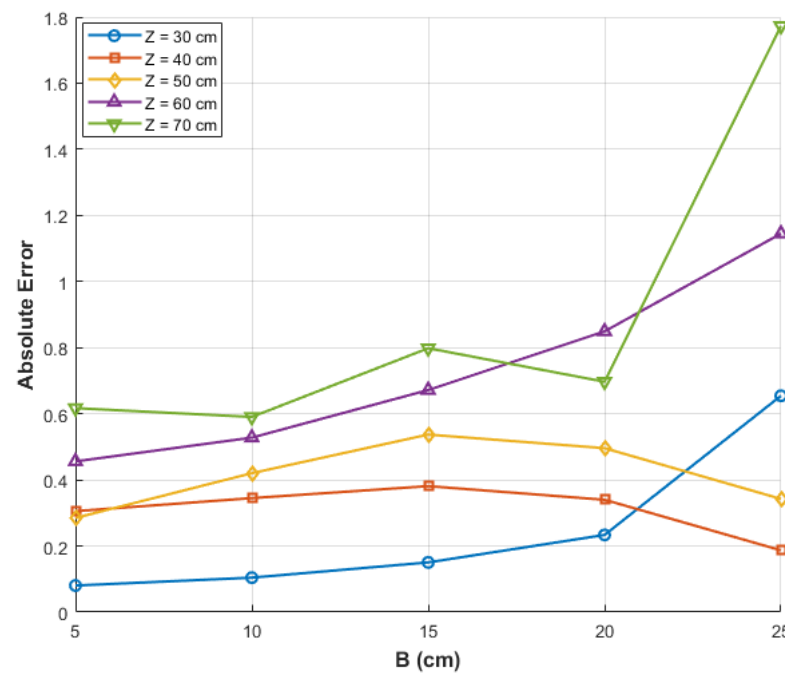


Figure 9. Impact of B on systematic error at different Z .

Based on Figure 8, it can be observed that when the K value, defined as B/Z , is less than 1, with the same baseline length, as the object distance Z increases, the K value gradually decreases, leading to an increase in measurement error. Conversely, as shown in Figure 9, when the object distance is constant, the change in measurement error is not significant as the baseline length increases. Combining the analyses of Figures 5 and 8, we can infer that when the K value is less than 1, the variation in object distance is the primary factor affecting measurement error. Therefore, to maximize measurement accuracy in a binocular measurement system, the camera should be positioned as close to the object as possible in this scenario. When the K value is greater than 1, the primary factor affecting measurement accuracy is the change in baseline length, which should be controlled within a certain range. Overall, when designing a binocular measurement system, the ratio of object distance to baseline length should be set within the range of 1 to 1.5 to ensure optimal imaging results.

4.2.2. Experiment II

The binocular measurement system setup for Experiment II, as illustrated in Figure 10, is largely similar to that of Experiment I. With a fixed object distance Z of 500 mm and a baseline length of 100 mm; the angle between the baseline and the optical axis was adjusted to 5° , 15° , 25° , 35° , 45° , and 55° , respectively.

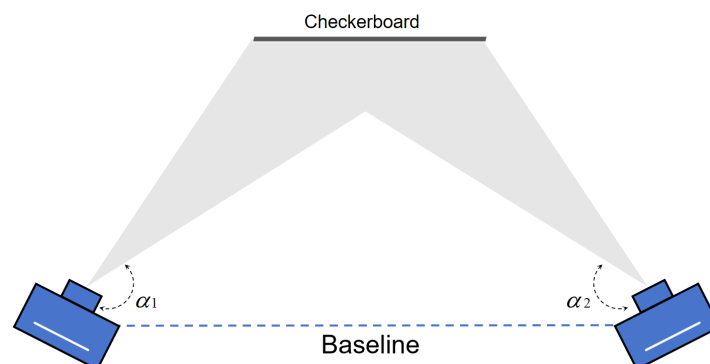


Figure 10. Plan view of experimental apparatus.

The measurement results and error curves are presented in Table 2 and Figure 11. It shows that the measurement error is minimized when the camera angle is 35 degrees. As the angle increases from 0 to 35 degrees, the measurement error decreases. However, when the angle exceeds 35 degrees, the measurement error gradually increases. This trend is consistent with the simulation results shown in Figure 4a.

Table 2. Measurement results of target (unit: mm).

Angle	5°	15°	25°	35°	45°	55°
result	28.0896 mm	26.3043 mm	26.7151 mm	27.1043 mm	27.3276 mm	27.433 mm

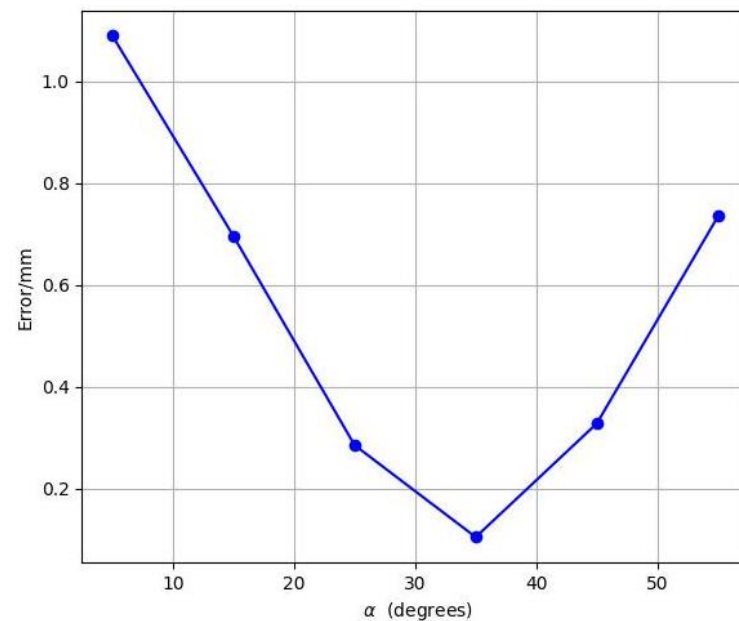


Figure 11. Measurement error curves of angle α between baseline and optical axis.

5. Conclusions

This paper discusses an investigation of structural system parameters in binocular stereo vision systems that are prone to causing measurement errors. First, by establishing a binocular vision error analysis model and deriving the corresponding system error calculation formulas, this study analyzes and discusses how structural parameters, such as baseline distance, object distance, and the angle between the camera's optical axis and the baseline, affect measurement accuracy. Secondly, through experimental design, the effectiveness of the error functions for the structural system parameters studied in this paper is validated. Specifically, when the ratio of baseline length to object distance is between 1 and 1.5, and the angle between the baseline and the optical axis is between 30 and 40 degrees, the system demonstrates high measurement accuracy with minimal error. This provides guidance for the research and design of subsequent binocular vision systems. In future research, we will focus on the design of an underwater binocular camera system to ensure that the binocular stereo vision measurement system can operate effectively and accurately under complex optical conditions, including low light, refraction, and scattering underwater.

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Conflicts of Interest: Author Jinwei Gu was employed by the company Ganyu Agricultural Development Group Co., Ltd., China. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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