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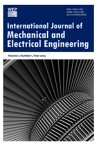

Comprehensive Review of Camera Calibration Methods for Three-dimensional Imaging Technology

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ABSTRACT

Through a systematic review of relevant literature, this paper comprehensively elucidates the evolution of camera calibration techniques and analyzes key milestones in its development. It introduces traditional camera calibration, self-calibration, and neural network-based camera calibration methods along with their research status, summarizing the characteristics and applicable scenarios of each method in practical applications. Based on the latest research progress, it delineates the latest technologies and methods in the field of camera calibration, highlighting their respective advantages and limitations. Prospects for the future development of camera calibration techniques are provided, exploring potential breakthroughs in high-precision, high-robustness mapping models, and automatic, accurate marking of image feature points, thereby offering valuable insights for addressing complex scenarios in 3D measurement applications.

KEYWORDS

Camera Calibration; Three-dimensional Imaging; Neural Networks.

1. INTRODUCTION

In the field of 3D camera measurement and computer vision, camera calibration technology plays a crucial role. One of the key issues is establishing the correspondence between 3D world coordinates and 2D image coordinates. Currently, camera calibration methods include traditional camera calibration, camera self-calibration, and neural network-based calibration. Traditional camera calibration is based on geometric principles and camera models. It remains in use because its physical models are highly universal and robust, making it more reliable in complex scenarios or less-than-ideal conditions. Camera self-calibration does not rely on pre-known camera parameters, making it adaptable to a variety of scenarios and robust against noise and outliers. Neural network-based calibration can automatically learn complex feature representations and patterns, providing a certain level of adaptability to various types of cameras and scenes.

This paper analyzes and summarizes the traditional calibration methods and self-calibration techniques, with a focus on neural network-based calibration methods. It explains the principles behind each type of calibration, outlines the latest developments in these calibration methods, provides a summary of the whole paper, and looks ahead to the future prospects for the development of each calibration method.

2. TRADITIONAL CAMERA CALIBRATION

Traditional camera calibration is a method for estimating camera parameters by capturing images of calibration patterns or special designs with known geometric structures. By establishing correspondences between points with known coordinates on the calibration object and their image projections, certain algorithms are used to derive the intrinsic and extrinsic parameters of the camera model. Traditional camera calibration methods include the Direct Linear Transformation method, the two-step method, and the Zhang's calibration method.

Table 1. Traditional Camera Calibration Methods.

Traditional camera calibration methods.	advantage	disadvantage	Applicable scenarios and scope
Direct-linear transformation method	1. Simple and easy to implement, with a clear theoretical foundation. 2. Requires minimal special requirements for calibration boards, resulting in lower costs.	1.Accuracy is greatly affected by noise and systematic errors. 2. Requires a large amount of calibration data and complex mathematical computations.	1. Suitable for calibrating the intrinsic parameters of cameras, such as focal length and principal point position. 2. Applicable to general calibration tasks where extremely high accuracy is not required.
Two-step method	More flexible and more accurate	1. Requires high-precision alignment between the camera and measurement equipment, leading to higher costs. 2. Calibrating extrinsic parameters requires accurate 3D spatial points, making data acquisition relatively challenging.	1. Suitable for camera calibration tasks requiring higher accuracy, such as in mapping, engineering surveying, and related fields. 2. Imposes certain requirements on equipment and data preparation, making it suitable for professional calibration tasks
Zhang Zhengyou calibration method	1. High accuracy and good robustness. 2. Suitable for various calibration boards and scenarios.	1. Requires the prior preparation of special calibration boards, with a need to ensure that the feature points on the boards can be accurately detected. 2. Involves substantial computational load, leading to longer calculation times.	1. Suitable for camera calibration tasks requiring high accuracy, such as in computer vision and 3D reconstruction. 2. Imposes certain requirements on calibration boards and data preparation, making it suitable for professional calibration tasks.

2.1. Direct-linear Change Method

Abdel-Aziz and Karara proposed the Direct Linear Transformation (DLT), an algorithm that explores the relationship between images and object space without requiring initial values for the intrinsic and extrinsic camera parameters, making it relatively straightforward. It is one of the most widely used methods among linear calibration techniques[1].

To reduce errors arising from the Direct Linear Transformation method, researchers have proposed various improvements. Optimization techniques, including iterative algorithms or camera pose estimation algorithms, have been used to enhance the DLT matrices or optimize the DLT algorithm, thereby improving calibration accuracy. In 2019, Wu Jinming and colleagues improved the DLT algorithm by introducing a transformation matrix constraint via the RAC model, maintaining the high real-time capability of the DLT algorithm while increasing pose calculation accuracy[2]. In 2020, Barone et al. proposed a calibration method that incorporates anisotropic uncertainty information through a weighted DLT algorithm to improve calibration accuracy[3]. In 2021, Zhang Lei and Zhang Tianyi introduced an improved object pose estimation method by optimizing the DLT process and incorporating nonlinear optimization to enhance precision[4]. In 2023, Chen Yang proposed a control field-based camera calibration method, where the DLT algorithm is used to obtain initial camera parameter values, followed by the Levenberg-Marquardt (L-M) optimization method to solve for optimal model parameters[5].

Adding control points: Increasing the number of control points on the calibration board can improve calibration accuracy. In 2020, Li Qinwen and colleagues addressed the issue of low accuracy in the traditional DLT method when the range of target point movement is limited by introducing laser ranging data[6]. In 2021, Akinori, inspired by the DLT method, proposed an omnidirectional camera-based calibration and 3D reconstruction method, expanding the camera's field of view[7].

2.2. Two-step Method

The two-step method, proposed by Tsai in 1986, is a calibration algorithm that, while accounting for radial distortion, remains widely applicable in practice[8]. The process for this algorithm is as follows: In the first step, the intrinsic and extrinsic parameters of the camera are computed. In the second step, radial distortion factors are introduced, and optimization algorithms are used to combine the results from the first step with radial distortion factors to achieve more precise outcomes.

Researchers have studied the calibration accuracy of the Tsai algorithm, introducing nonlinear optimization algorithms (such as least squares and weighted iterative methods) in the second step of the Tsai calibration process to precisely optimize the camera's intrinsic parameters and reduce calibration errors. In 2010, Xu Jie proposed an improved calibration method based on area-array CCD cameras and a comprehensive distortion model, using an iterative approach to converge to the exact value, addressing the Tsai method's limitation of not being able to calibrate all intrinsic and extrinsic parameters in a single pass[9]. In 2012, Mi Xue et al. used a nonlinear camera model with distortion, combining least squares with nonlinear equations to enhance calibration accuracy and mitigate the cumbersome nature of nonlinear optimization[10].

Furthermore, many researchers have drawn inspiration from the two-step method to propose new calibration approaches. For example, in 2022, Yao Longxing, drawing from Tsai's planar camera calibration algorithm, proposed a new calibration method that separates the camera's intrinsic and extrinsic parameters from the camera model's distortion parameters, enhancing calibration speed and accuracy[11]. In 2023, Liu Zeqing et al. introduced a calibration method based on onboard marker targets, employing simulated annealing sparrow search to solve for high-speed camera intrinsic and extrinsic parameters, enhancing long-range calibration accuracy and intersection measurement precision[12].

2.3. Zhang Zhengyou Calibration Method

Zhang's calibration method is an algorithm proposed by Zhang Zhengyou in 1988 for camera calibration using a planar standard chessboard pattern. The key steps of this method involve placing the planar chessboard at various angles in space and capturing images with a camera. By extracting the corner points from the chessboard pattern in the images, the coordinate information is obtained. Then, these image coordinates of the corner points are compared with the known world coordinates of the chessboard to calculate the functional relationship between them. Through this relationship, the intrinsic and extrinsic parameters of the camera can be accurately determined[13].

Zhang's calibration method has the advantage of being simple and easy to calibrate but has some drawbacks, such as lower calibration accuracy and poor robustness. To effectively address these issues, many researchers have conducted extensive studies to apply optimization algorithms to Zhang's calibration method. For example, particle swarm optimization (PSO) can be used to find optimal values for camera parameters, and least squares can be used to fit the camera model, optimizing both intrinsic and extrinsic parameters. Additionally, the sparrow search algorithm has been used to optimize the estimation of camera parameters, enhancing calibration accuracy and robustness.

In 2019, Wang Linxia and colleagues applied chaos particle swarm optimization (CPSO) to Zhang's calibration method, improving the process of optimizing intrinsic and extrinsic parameters to achieve higher calibration precision[14]. In 2021, Tian Shaobing and colleagues proposed a camera calibration algorithm based on an improved particle swarm algorithm, combining dynamic inertia weight coefficients to iteratively optimize the initial intrinsic parameters obtained by Zhang's calibration method[15]. In 2022, Dan Xizuo et al. proposed a camera calibration method that automatically detects chessboard corner points using the EDLines algorithm, filtering straight lines at the corners where they break[16]. Also in 2022, Qu Kai and Guo Zhongyou improved Zhang's calibration method by using the total least squares algorithm to solve for the homography matrix, increasing accuracy[17]. In 2023, Shang Hai and colleagues proposed an improved sparrow search algorithm for camera calibration, combining the position update algorithm from the bird swarm algorithm with the position update formula from the sparrow search algorithm, to avoid local optima[18].

3. CAMERA SELF-CALIBRATION METHOD

The concept of camera self-calibration was introduced by Faugeras, Luong, and Maybank in the early 1990s[19]. The fundamental idea of camera self-calibration is to use a sequence of images captured by the camera from different positions or orientations, and then analyze and match the feature points within the image sequence to derive the camera's intrinsic and extrinsic parameters. This method primarily includes the self-calibration approach that directly solves the Kruppa equations, as well as the stratified incremental self-calibration approach.

Table 2. Camera Self-calibration Method

camera self-calibration method	advantage	disadvantage	applicable scenarios and scope
Self-calibration method based on the Kruppa equations	Simple and straightforward, with efficient computation.	1. Calibration accuracy is affected by many factors. 2. Requires high-quality input data, with sufficient and evenly distributed feature point pairs.	Used for camera self-calibration in simple scenarios, such as static scenes with limited camera movement.
Stratified incremental self-calibration method	Incrementally optimized, with strong robustness and high adaptability	1. Requires multiple iterations for optimization, leading to high computational complexity. 2. The performance of this method largely depends on parameter settings.	Suitable for camera self-calibration tasks in complex scenarios, such as when there is a high level of noise, mismatches, or nonlinear distortions.

3.1. Self-calibration Method Based on the Kruppa Equations

In 1992, Faugeras proposed the self-calibration method that directly solves the Kruppa equations. This method uses the feature points in multiple images captured by the camera to directly derive the intrinsic and extrinsic parameters by solving the Kruppa equations, without needing to first obtain the 3D coordinates of the feature points[20]. This approach simplifies the camera calibration process, avoiding the need for projective reconstruction of the image sequence, making the algorithm faster and more convenient.

To address the issue of low accuracy in the direct equation-solving calibration method, researchers have conducted studies both domestically and internationally. In 2015, Merras proposed a camera self-calibration technique using an improved genetic algorithm based on the Kruppa equations to avoid local minima in camera self-calibration[21]. In 2020, Yang Yanan and Jia Yuan introduced a camera self-calibration method based on an improved genetic algorithm, combining elite retention strategy, random tournament selection, and adaptive crossover and mutation probabilities to resolve premature convergence and stagnation in the parameter optimization process, thereby improving calibration accuracy[22].

To tackle the lack of robustness in traditional camera self-calibration algorithms based on the Kruppa equations, more robust feature point extraction algorithms (such as SIFT, SURF, etc.) and evolutionary algorithms (such as genetic algorithms) can be used to reduce misalignment and improve robustness. In 2012, Wang Xin and colleagues proposed a stepwise self-calibration method based on the Kruppa equations, using a genetic algorithm strategy to optimize the scale factor in the Kruppa system[23]. In 2016, Wang Junzhu et al. proposed a camera self-calibration method that uses a tensor voting algorithm to robustly screen SIFT-matched feature points. They obtained the camera parameter matrix based on the Kruppa equations and 3D reconstruction algorithms, achieving more robust and accurate camera parameters[24]. In 2019, Zhang Bolin and Liu Ronghai proposed a self-calibration optimization algorithm based on a multi-population genetic algorithm for the Kruppa equations, using the SIFT algorithm for feature point matching, while the multi-population genetic algorithm was used to improve the Kruppa equations, effectively enhancing the robustness of intrinsic parameter determination[25].

3.2. Stratified Incremental Self-calibration Method

To address the complexity and computational challenges of camera calibration, researchers have proposed the stratified step-by-step calibration method. This approach decomposes the camera calibration problem into two sub-problems: the camera's intrinsic parameters and extrinsic parameters. It then iteratively estimates the intrinsic parameters first, followed by the extrinsic parameters, and subsequently refines the intrinsic parameters based on the estimated extrinsic parameters. This process continues until convergence is achieved. Two typical approaches within the stratified step-by-step calibration method are the QR decomposition method and the absolute quadric method.

The absolute quadric self-calibration method, proposed by Triggs in 2000, is a solution to a set of self-calibration equations based on the absolute quadric[26]. This calibration method uses two approaches to solve the set of equations: the first involves solving with the Sequential Quadratic Programming (SQP) optimization algorithm, which allows full camera calibration with at least three images; the second employs a semi-linear method, which requires at least four images for full camera calibration. The advantage of this method compared to the two previously mentioned methods is that it can unify multiple images into a single projective frame, ensuring consistency across all images on the plane at infinity.

To improve the robustness and accuracy of this self-calibration method, Chen Jing in 2012 proposed a multi-viewpoint global optimization approach based on LMI (Linear Matrix Inequality) relaxation techniques, treating a fixed focal length as an independent unknown variable and incorporating it into the objective function of the absolute dual quadric's fundamental imaging constraint equation, leading to a globally optimal solution for the focal length[27]. In 2014, Wu Xiaojun and Fan Dongkai proposed a new self-calibration method based on semidefinite programming. This method ensures the semidefinite property and feasible domain constraints of the absolute dual quadric, ensuring that the DIAC (Dual Image of the Absolute Conic) decomposition yields the intrinsic parameter matrix[28]. In 2020, Yang Duo and colleagues proposed a sequential image reconstruction model with a specific angle, incorporating the absolute dual quadric method into sequential self-calibration[29].

4. NEURAL NETWORK-BASED SELF-CALIBRATION METHOD

The concept of neural network learning was first proposed by Hebb in 1949; LeNet was the first fully-fledged convolutional neural network; AlexNet introduced features like ReLU, Dropout, and LRN into CNNs, driving the development of deep neural networks; ZFNet solved the feature map visualization problem, advancing the progress of deep neural networks; VGGNet achieved higher accuracy by increasing the network's depth; GoogLeNet introduced the Inception Model, further enhancing accuracy. ResNet took the idea of repeating modules to a deeper level; as the number of deep neural network layers continued to increase, the need for more parameters made it difficult to maintain accuracy, prompting the emergence of DenseNet to address this issue.

To address issues like slow convergence of neural network weights and thresholds, and low calibration accuracy, scholars have proposed two types of improvement methods: one involves optimizing the neural model, and the other focuses on optimizing thresholds and weights to enhance convergence speed. In 2011, Yuan Sicong and Jiang Xiangkui proposed using a genetic algorithm to train a BP neural network, utilizing the genetic algorithm to optimize the network's weights and thresholds[30]. In 2021, Chen Wenyi and colleagues proposed a camera calibration method based on dual neural networks, simplifying the imaging model into two functional relationships, optimizing the BP algorithm with the PSO (Particle Swarm Optimization) algorithm, and constructing two neural network models to accomplish camera calibration[31]. In 2022, Hu Zhixin and Wang Tao used an improved genetic algorithm to optimize the BP neural network, applying dynamic crossover and mutation probabilities to enhance the convergence speed and reprojection accuracy[32]. The same year, Cao Yuwei and colleagues proposed a non-model-based stereo calibration method for binocular fisheye cameras using neural networks, which implicitly describe the nonlinear mapping relationship between image coordinates and scene space coordinates to model distortion effectively[33]. In 2023, An Hailin and Liu Ji introduced a BP neural network optimization method based on an improved genetic simulated annealing algorithm, improving BP network performance by refining the fitness scaling, crossover, mutation probabilities, and annealing criteria[34].

Many researchers have combined deep learning with neural network calibration methods. For instance, in 2019, Xiang Peng and colleagues proposed a camera calibration method based on a deep neural network that does not require data feature extraction or classification. It uses deep learning techniques for target segmentation and measurement feature point extraction, achieving flexible high-precision calibration in complex environments within a planar area[35]. In 2023, Song Le and colleagues proposed a monocular vision measurement method for cuboid 3D measurements based on Mask-RCNN (Region-Based Convolutional Neural Network) and Structure from Motion (SFM). This method automates 3D measurements from a single viewpoint through deep learning techniques, combining neural networks with image processing to extract measurement points[36]. Shen Shiyu and colleagues proposed a convolutional neural network-based deep learning model for 3D spatial distribution reconstruction of microscopic particles in a light field, using numerical simulation to create a 'particle spatial distribution-light field image' dataset, enabling experimental reconstruction of particle distribution in laminar flow within a horizontal microchannel[37].

5. SUMMARY

This article provides a comprehensive review of three types of calibration methods, summarizing relevant literature and explaining the technical principles and development trends of each camera calibration method. As research progresses, various techniques continue to advance, aiming for greater accuracy and robustness while gradually reducing reliance on traditional mathematical models. The development of neural network-based calibration methods, in particular, offers more ideas and solutions for camera calibration, often outperforming traditional calibration methods.

The future development of camera calibration methods can be summarized in two key points:

Develop or improve a method that simultaneously enhances calibration accuracy and ensures robustness. Currently, researchers tend to focus on either improving the accuracy of a single calibration method or enhancing its robustness, but there hasn't yet been a comprehensive calibration method that balances simplicity, high accuracy, and robustness. The goal for the future is to create a calibration algorithm that considers multiple factors, improving accuracy while maintaining robustness in complex and changing scenarios. Additionally, lightweight neural network architectures like MobileNet and ShuffleNet can be used to reduce the number of model parameters and computational complexity, enhancing the speed of feature point extraction.

Create an integrated deep learning and camera calibration model. In recent years, deep learning technologies have made significant strides in the field of computer vision. Currently, deep learning-based camera calibration methods typically use traditional parameterized camera models. However, these models have limitations when dealing with complex scenes due to their constraints. Non-parameterized camera models, on the other hand, don't have these restrictions, as each pixel is associated with a corresponding 3D incoming light ray. Combining neural networks with deep learning models can help handle complex nonlinear mapping relationships, leading to more accurate modeling of the intrinsic and extrinsic parameters of a camera. The integration of camera calibration and deep learning allows for automatic learning of key features in images without manually defining or extracting feature points, increasing the level of automation in calibration and reducing the need for human intervention.

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