Application of super-resolution camera calibration method in DIC measurements

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ABSTRACT

Camera calibration is an important component of stereo digital image correlation (DIC) measurements. However, traditional calibration images suffer from insufficient information and blurriness during corner detection at low resolutions, which limit the precision of calibration and measurement. To address this issue, a super-resolution corner detection method based on attention mechanism is proposed in this paper. The proposed method enhances the focus on the high-frequency information of calibration corners using attention mechanism, thereby enabling the reconstruction of low-resolution images to improve the accuracy of corner detection during calibration, thus enhancing the quality of camera calibration. Experimental results on DIC camera calibration reveal that the proposed corner detection method exhibits smaller reprojection errors. Furthermore, the calibration results using this method can improve the geometric reconstruction accuracy of DIC.

Keywords: digital image correlation, camera calibration, super-resolution reconstruction, attention mechanism, corner detection.

1. INTRODUCTION

Stereo-digital image correlation (Stereo-DIC) technology is a noncontact optical measurement method that measures an object's displacement or deformation by analyzing the markers on its surface in continuous images. Due to its high precision and flexibility, this technology is widely used in the measurement of material deformation. Stereo-DIC, as an optical method rooted in binocular stereo vision and image processing, encompasses two fundamental technologies: binocular camera calibration [1] and stereo digital image correlation [2]. In Stereo-DIC, binocular camera calibration is not only important for the applicability of this technique but also has a significant impact on the final measurement's accuracy [3]. Therefore, relevant research on binocular camera calibration is of great significance for improving the measurement precision of Stereo-DIC.

In 1999, Zhang proposed a two-dimensional (2D) planar calibration board for obtaining the internal and external parameters of a camera, as well as its distortion coefficients, based on the known dimensions of the calibration board [4]. This method has been widely used due to its simplicity and high precision. Zhang's calibration method involves positioning 2D calibration targets with distinct characteristics, such as squares [4], checkerboards [5], and circles, in various orientations, then capturing them using two cameras. Achieving a precise match between the control points (corner points or center points) on the calibration targets in the captured images is crucial. Utilizing these control points for alignment enables accurate calibration and computation of the parameters in the stereo vision system. However, these 2D targets with specific features also have some limitations [6]. In particular, the calibration method requires a high-precision feature point detection method. To address this issue, increasing the resolution of the calibration image can be considered, referring to the technique of constructing a high-resolution (HR) image from one or more low-resolution images that already exist in the same scene (i.e., image super-resolution reconstruction) [7]. Enhancing corner detection accuracy involves focusing on high-frequency details surrounding the corner during super-resolution reconstruction. The Harris corner detection method requires the calculation of the local structure matrix and eigenvalues of pixels, thus leading to high computational cost on large-scale images. Additionally, the use of a higher pixel camera to increase the resolution of the calibrated image inevitably increases the cost.

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The present paper introduces an attention-based super-resolution corner detection method. Through super-resolution reconstruction using a specialized network, high-frequency details and low-frequency background are effectively processed using an attention mechanism. By calculating gradients and eigenvalues of HR image pixels, corner point detection accuracy and camera calibration are improved. This is then applied to the static reconstruction of DIC.

2. PRINCIPLE OF CALIBRATION

To ensure accurate DIC measurements, it's crucial to establish the relationship between image pixels and scene positions. This involves determining camera model parameters by matching feature points in image coordinates with their counterparts in world coordinates, as outlined in the imaging model. Zhang's calibration method [4] employs a chessboard pattern for calibration, allowing the extraction of internal and external camera parameters by identifying corner points and measuring their positions on the image plane. Hence, the precision of corner detection algorithms significantly impacts camera calibration. The attention-based super-resolution corner detection algorithm proposed here utilizes attention mechanisms to detect high-frequency information from the alternating edges of the chessboard pattern, enhancing calibration accuracy by reconstructing high-resolution images with richer corner features. The process is depicted in Figure 1.

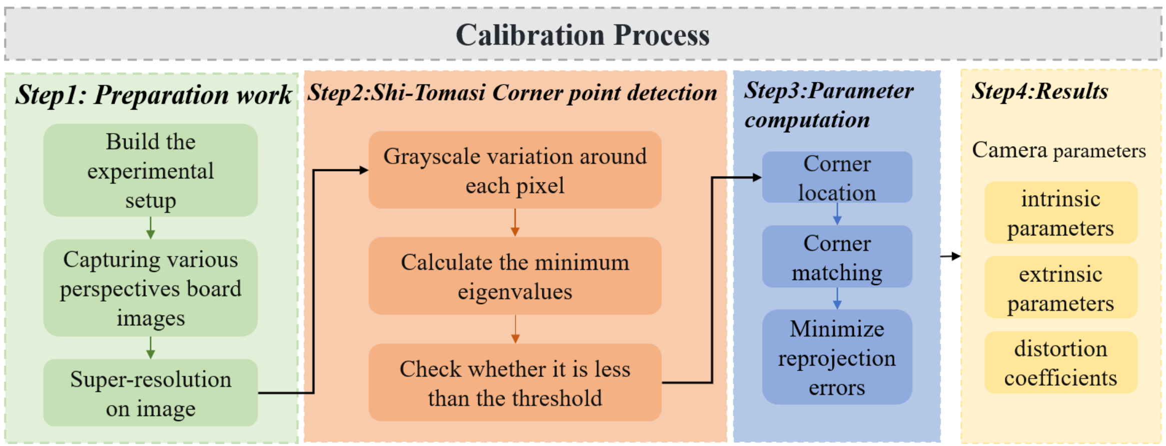

Figure 1. The calibration process.

2.1 Super-resolution model

The super-resolution network, incorporating an attention mechanism [8], comprises three core components: a feature extraction module, an information extraction module, and a reconstruction module. The feature extraction module discerns features from the initial low-resolution image, while the information extraction module dynamically adjusts feature expressiveness using a mapping attention mechanism to enhance the retrieval of finer details like contour textures. Following this, the reconstruction module executes element-wise addition operations on the gathered high-resolution information, facilitating the transformation from low-resolution (LR) input images to high-resolution (HR) output images. The model's structure is depicted in Figure 2.

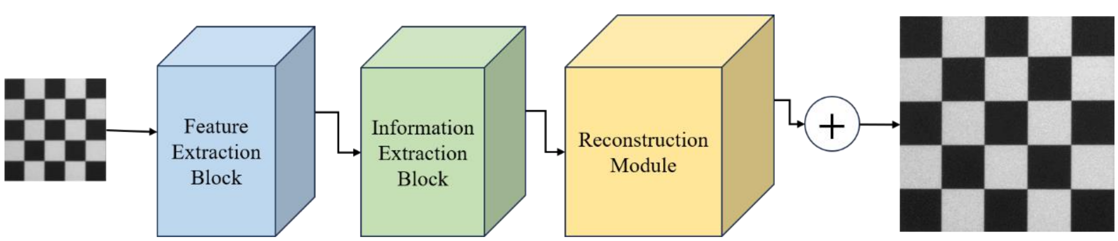

Figure 2. Super-resolution reconstruction model.

The information extraction block used in this paper consists of two 3×3 convolutions, both with feature dimensions of 64. The processing involved is described as:

$$F_0 = H_{FE}(I_{LR}) \tag{1}$$

where I_{LR} represents the input low-resolution image, H_{FE} denotes the function used for feature extraction, and F_0 represents the extracted features that will be utilized in the subsequent stage of processing. The feature extraction block employs a feature map attention mechanism to prioritize global information, enhancing the model's focus and feature representation. This integration of local and global features results in more effective and comprehensive feature extraction.

The information extraction block [8] is comprised of three subunits sharing a similar architecture, each employing the feature map attention mechanism. The comprehensive structure of the information extraction unit can be segmented into an information enhancement unit and a compression unit, illustrated in Figure 3. The processing procedure can be described as follows:

$$F_i = H_i(F_{i-1}), i = 1, 2, \ldots, n \tag{2}$$

where H_i denotes the function that performs the feature extraction, and F_i is both the output of the current information extraction block and the input of the next information extraction block.

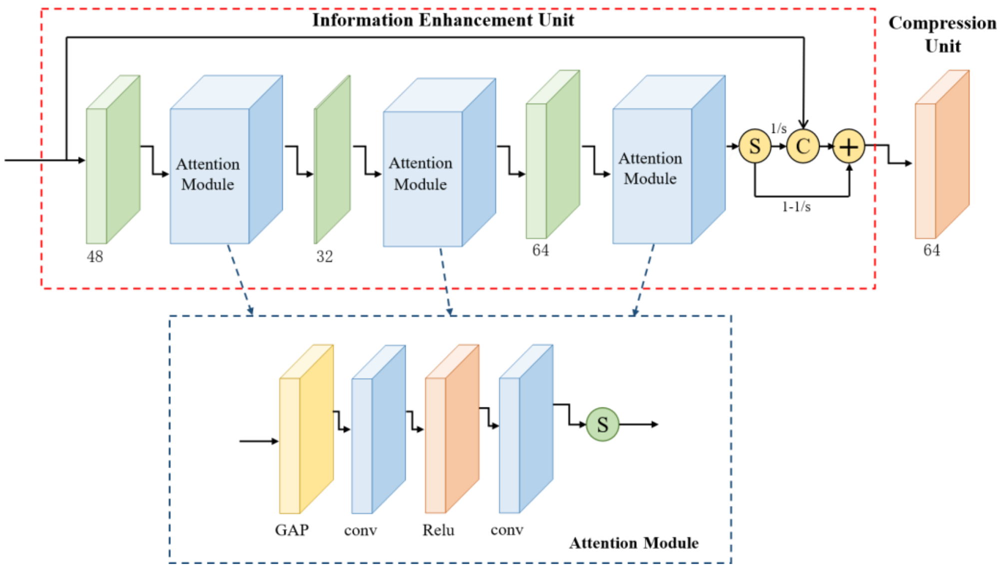

Figure 3. Information extraction block.

The attention module identifies and prioritizes features crucial for the task at hand, enhancing the network's discriminative ability. In chessboard pattern image calibration, high-frequency corner point information is vital. Therefore, an attention mechanism is introduced to emphasize high-frequency channel details while minimizing redundant information from low-frequency areas, such as edges and textures.

For HR image reconstruction, the module uses features from prior convolutional layers and applies them to the low-resolution image scale. ESPCN [9], known for its efficiency in super-resolution, ensures superior results with faster computation and fewer parameters. It's ideal for scenarios with limited computational resources. Its network is depicted as:

$$I_{SR} = H_{REC}(H_i(F_{i-1})) + U(I_{LR}) \tag{3}$$

where H_{REC} and U denote the reconstruction module and the bicubic interpolation operation, respectively, and I_{SR} denotes the final output.

2.2 Corner detection

Corner point detection is required for the super-resolution reconstructed calibration images to achieve high-precision camera calibration. Compared with the Harris corner point detection algorithm, the Shi-Tomasi algorithm [10] shows an improved performance in terms of computational efficiency and stability. In particular, the Shi-Tomasi corner detection algorithm defines a pixel point as a corner point by calculating the response function $R = \min(\lambda_1, \lambda_2)$, when the value of R is greater than a set threshold. In addition, λ_1 and λ_2 are the eigenvalues of the autocorrelation matrix M with local gray scale variation. Here, M is denoted as:

$$M = \sum w(x, y) \nabla I \nabla I^T \tag{4}$$

where $w(x, y)$ is a window function to weigh the gray-scale changes in the local region, ∇I is the gradient vector of the image at pixel point (x, y), and ∇I^T is its transpose.

3. EXPERIMENTAL ANALYSIS

In order to verify the calibration accuracy of the proposed method and the application accuracy in the actual test of DIC, this paper uses calibration experiments and DIC measurement experiments to verify it. To achieve better image reconstruction results, the magnification factor should not be too large or too small. In this case, it is necessary to consider both computational complexity and the goal of preserving sufficient image details. Therefore, the image was upscaled by a factor of 2×2 for super-resolution to strike a balance between these factors.

3.1 Camera calibration experiment

Reprojection error evaluates camera calibration quality; smaller errors indicate closer calibration to real data. Here, the reprojection errors under the two methods were compared by using the calibration methods based on the Harris corner detection approach and on super-resolution corner detection proposed in this paper to calibrate the calibration plate images captured under the same position. Super-resolution increased image resolution from 1624×1234 to 3248×2468 pixels, as depicted in Figure 4. Table 1 compares parameters calculated by both methods.

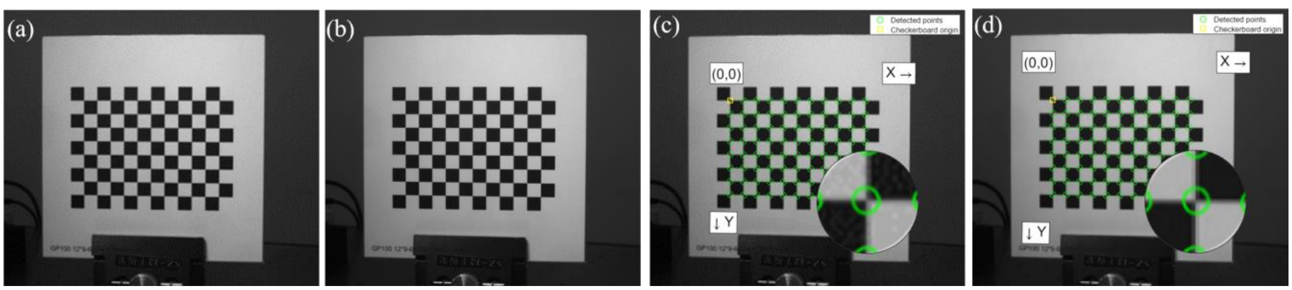

Figure 4. Images before and after super-resolution reconstruction. (a) Original image; (b) Super-resolution reconstructed image; (c) Original image corner detection; (d) Corner detection based on super-resolution reconstruction.

Table 1. Calibration parameters calculated by Harris corner detection and the proposed method.

Binocular camera parameter		Left camera parameter		Right camera parameter	
Harris	**This paper**	**Harris**	**This paper**	**Harris**	**This paper**
R_x=0.0017	R_x=0	k_1=-0.19	k_1=-0.21	k_1=-0.21	k_1=-0.21
R_y=-0.3596	R_y=-0.3598	k_2=1.83	k_2=1.96	k_2=2.91	k_2=2.89
R_z=0.0001	R_z=0.0002	f_x=2892.51	f_x=5788.09	f_x=2899.77	f_x=5795.97
T_x=94.3598	T_x=94.3789	f_y=2892.87	f_y=5788.94	f_y=2900.99	f_y=5798.31
T_y=-0.3254	T_y=-0.3949	C_x=825.05	C_x=1648.63	C_x=799.11	C_x=1596.33
T_z=16.3666	T_z=15.9746	C_y=621.09	C_y=1241.43	C_y=619.99	C_y=1238.92

Referring to the corresponding values of the optimal calibration data, the reprojection errors of the Harris calibration method and the proposed calibration method in this paper can be obtained, as shown in Figure 5.

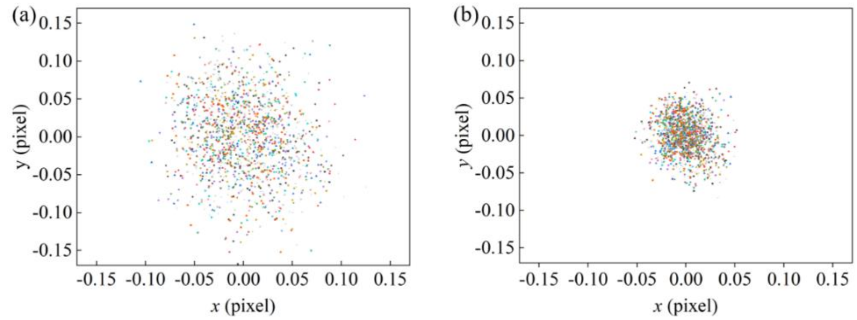

Figure 5. The reprojection errors under different calibration methods. (a) Error obtained by the Harris corner detection calibration method and (b) Error obtained from the corner detection calibration method proposed in this article

The calibrated reprojection error obtained under Harris is within 0.15 pixel and the average reprojection error is 0.0561 pixel, and the calibrated reprojection error of the proposed method is within 0.08 pixel and its average reprojection error is 0.1031 pixel. Due to the super-resolution magnification of 2×2, the actual distance corresponding to each pixel point is 0.25 times of the original image. Within the same pixel scale, the reprojection error of the proposed method should be 0.0267 pixel, and its reprojection error is reduced by 47.6%.

3.2 DIC measurement experiment

The experimental setup shown in Figure 6(a) was built to verify the effectiveness of the proposed preprocessing based on super-resolution angular point detection calibration method for DIC testing. The resolution of the camera is 1624×1234 pixels with a 25 mm focal length lens; the calibration plate was a 12 × 9 tessellated grid calibration plate, with the width of a single grid being 6 mm. In this experimental environment, the camera calibration results obtained using different methods in the same camera pose were used to perform geometric reconstruction on the nominal size 60mm standard gauge block shown in Figure 6(b).

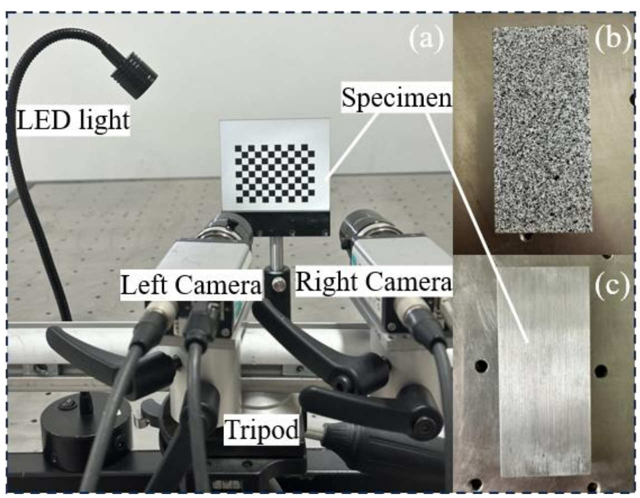

Figure 6. The experimental environment. (a) Experimental setup, (b) 60 mm standard measuring block, and (c) 60 mm standard measuring block for manual spot making.

The search step size was set to 7 pixels, while the search subset size was configured at 21×21 pixels. The geometric reconstruction of the 60 mm standard gauge block in Figure 6(c) was performed using calibration results obtained from the Harris corner detection calibration method and super-resolution corner detection calibration method under the same camera pose. First, one image each was taken with a binocular camera, after which the IC-GN algorithm [11] was used to perform correlation analysis on the two images. Finally, the pixel coordinates were converted into physical coordinates using calibration parameters to calculate the actual measurement results of the standard gauge block.

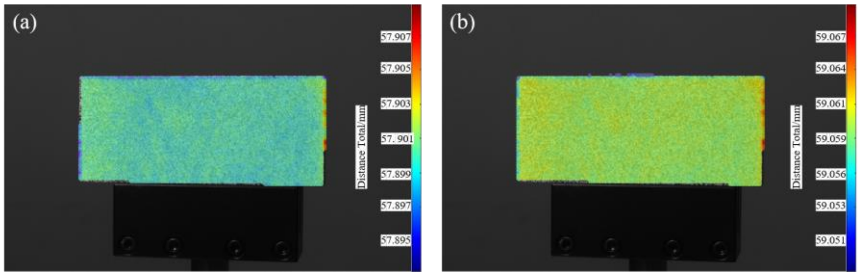

Figure 7. Geometric reconstruction effect. (a) Measurement results of calibration method based on the Harris corner detection method and (b) Measurement results based on the calibration method proposed in this article.

Figure 7(a) shows the calibration method using Harris corner detection, while Figure 7(b) shows the reconstruction results of the proposed super-resolution corner detection calibration method. The reconstructed size of the gauge block based on the Harris corner detection calibration is 57.9008 mm, whereas the proposed calibration method yields a reconstructed size of 59.0588 mm. This results in a relative error decrease from 3.625% to 1.593%, and a reduction in deviation from 2.0992mm to 0.9412mm. These findings demonstrate that the proposed super-resolution corner detection calibration method enhances the reconstruction accuracy of DIC.

4. CONCLUSION

This article proposes a corner detection method for super-resolution calibration boards based on attention mechanism. The experimental results demonstrate that the proposed method can significantly improve the calibration accuracy of DIC cameras. In particular, the calibration results based on this method improve the accuracy of geometric reconstruction of the volume block compared with the traditional Harris corner point detection method. Therefore, a solution is found to improve the measurement accuracy of the DIC system.

REFERENCES

[1] Cui, Y., Zhou, F. Q., Wang, Y. X., Liu, L. and Gao, H., "Precise calibration of binocular vision system used for vision measurement," Opt. Express 22, 9134-9149 (2014).

[2] Pan, B., Yu, L. P., Zhang, Q. B., "Review of single-camera stereo-digital image correlation techniques for full-field 3D shape and deformation measurement," Sci. China Technol. Sci. 61(1), 1-20 (2018).

[3] Genovese, K., Chi, Y., Pan, B., "Stereo-camera calibration for large-scale DIC measurements with active phase targets and planar mirrors," Opt. Express 27, 9040 (2019).

[4] Zhang, Z., "A flexible new technique for camera calibration," IEEE Trans. Pattern Anal. Mach. Intell. 22, 1330–4 (2000).

[5] Ge, P. X., Wang, H. Q., Wang, Y. H., Wang, B., "Calibration of ring multicamera system with transparent target for panoramic measurement," IEEE Sens. J. 22(23), 23154-23164 (2022).

[6] Chen, B., Pan, B., "Camera calibration using synthetic random speckle pattern and digital image correlation," Opt. Lasers Eng. 126, 105919 (2020).

[7] Roger, T., Thomas, Y, Huang, S., "Multiframe image restoration and registration," Multifr. Image Restor. Regist. 1, 317-339 (1984).

[8] Wang, Z., Chen, J., Hoi, S. C. H., "Deep learning for image Super-Resolution: a survey," IEEE Tran. Pattern Anal. Mach. Intell. 43(10), 3365-3387 (2021).

[9] Dong, C., Chen, C. L., Tang, X. O., "Accelerating the super-resolution convolutional neural network," Computer Vision–ECCV 2016: 14th European Conference 391-407 (2016).

[10] Bansal, M., Kumar, M., "An efficient technique for object recognition using Shi-Tomasi corner detection algorithm," Soft Comp. 25, 4423-4432 (2021).

[11] Su, Y., Zhang, Q., Xu, X., "Interpolation bias for the inverse compositional Gauss–Newton algorithm in digital image correlation," Opt. Lasers Eng. 100, 267-278 (2018).