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A Study on Camera Lens Distortion Coefficients Estimation and Correction Technology Optimized for Image Region

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Abstract

The use of camera images for estimating object locations and distances has increased substantially, resulting in greater sensitivity to image distortion caused by camera lenses. Existing approaches to estimating and correcting lens distortion coefficients are limited because they apply uniform corrections to the entire image. This study introduces a method that enhances correction performance by approximately 30 percent compared to conventional techniques by estimating lens distortion coefficients for individual regions within the image and correcting objects within those regions. The proposed approach enables the accurate estimation of two-dimensional coordinates for target objects in specific image regions, yielding significantly improved image quality when the entire image is divided into regions and corrected sequentially.

Keywords: *lens correction, lens distortion, regional lens distortion coefficient, regional correction*

1. Introduction

In image processing and computer vision, camera lens distortion significantly impacts accuracy. In particular, 3D camera position estimation technology using multiple camera images is essential in diverse fields such as robot navigation, autonomous driving systems, and augmented reality. [1] Meanwhile, camera lens distortion during image capture can cause 2D image distortion and significantly reduce the accuracy of 3D position estimation. Specifically, radial and tangential distortions occur in mobile devices, low-cost lenses, and wide field-of-view environments, necessitating the correction of image distortion before processing. [2], [3] In robotic vision, the accuracy of the camera's internal parameters is a critical factor in precision control processes such as hand-eye calibration. [4]

Various lens distortion correction models are used to estimate lens distortion coefficients to determine the degree of lens distortion. However, simple models often struggle to represent the complex, high-order distortions of real lenses, resulting in poor accuracy, particularly in the outer regions of the lens. Meanwhile,

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to estimate lens distortion coefficients, multiple images, such as a chessboard, have been taken from arbitrary positions and poses to estimate the lens distortion coefficients of a lens distortion model. [5] Research is also being conducted on estimating lens distortion coefficients through neural networks and on various lens models. [6], [7]

Existing lens distortion estimation and correction methods include global correction, which estimates a single set of distortion coefficients applied to the entire image using a chessboard-like correction pattern captured across the entire camera field of view. This method attempts to minimize the average distortion error across the entire image, but fails to achieve optimal correction performance when distortion characteristics differ between the center and periphery of the image. Recent research has focused on neural lens models, which directly learn the physical characteristics of lenses from data. Research has also combined geometric projection principles and radial distortion models to directly derive distortion coefficients and camera parameters from a single image using linear equations. [8], [9] Spatially varying Distortion model methods are advanced models that take advantage of the fact that lens distortion is not uniform across an image but varies depending on location. They compute a different distortion vector for each pixel or use complex mathematical models such as B-splines to generate a continuous distortion map across the entire image. While highly accurate, these methods suffer from the complexity of the model and high computational cost. [10] Model-free or line-based methods correct distortion by analyzing the bending of straight lines in an image without using a distortion model. It can only be applied if there are enough straight-line components in each image. [11]

In this paper, we compared and analyzed the distortion coefficients of OpenCV's radial and tangential models. Using these distortion coefficients, we compared the distortion correction performance of a chessboard image, commonly used for distortion coefficient estimation, with the number of intersections and the distance between the camera and the chessboard image. Furthermore, while conventional methods estimate lens distortion coefficients for the entire camera image and then use these distortion coefficients to correct the distorted image, we proposed a novel method that estimates lens distortion coefficients using only target images from a specific region of the camera image and then uses these distortion coefficients to correct the distortion of that specific region. This method was then validated.

2. Estimation and correction of camera lens distortion coefficients

2.1 Lens distortion coefficient estimation model and estimation method

Camera lenses can introduce distortion into images due to their optical characteristics, reducing the accuracy of image processing. This distortion can be divided into two main types: radial distortion and tangential distortion. Radial distortion is a phenomenon caused by the lens's refractive index. It causes linearity to decrease with distance from the lens center, causing straight lines to appear curved. This distortion typically manifests as barrel distortion or pin cushion distortion. [12] Tangential distortion is a distortion in a specific direction that occurs when the lens and image sensor are not perfectly aligned.

To model complex lens distortion, an ideal pinhole model and a polynomial lens distortion model are used. To estimate camera lens distortion coefficients, multiple chessboard images are typically captured at different locations, and various camera parameters are estimated using OpenCV functions. That is, the two-dimensional coordinate values of the intersections of the black and white blocks of the chessboard are detected through the findChessboardCorners function and the cornerSubPix function in each image, and the camera intrinsic and extrinsic parameters and lens distortion coefficients are estimated using the calibrateCamera function, and these are used to correct the lens distortion of the camera image. [13] The following equations (1) and (2) are the basic camera lens distortion model equations of radial and tangential, respectively, and equation (3) is the lens distortion coefficients of the estimation target. $x_{distorted}$ is the two-dimensional coordinate of the distorted image, x and y are the 2D coordinates of the original image without distortion, and , $r = \sqrt{(x^2 + y^2)}$ is the distance from the optical axis.

$$x_{distorted,radial} = x(1 + k_1 r^2 + k_2 r^4 + k_3 r^6 + k_4 r^8 + k_5 r^{10} + k_6 r^{12}) \tag{1}$$

$$x_{distorted,tangential} = x + [2\, p_1 xy + p_2(r^2 + 2\, x^2)] \tag{2}$$

$$Distortion\ Coefficients = [k_1, k_2, k_3, k_4, k_5, k_6, p_1, p_2] \tag{3}$$

2.2 Method for correcting lens distortion and measuring correction error

OpenCV performs lens distortion correction using a model that integrates radial and tangential distortion. Typically, a basic lens distortion model uses a total of five coefficients, k_1, k_2, k_3, p_1 and p_2, where represent the radial distortion coefficients and the tangential distortion coefficients. In this paper, to precisely analyze the influence of lens distortion coefficients, we used an extended model that includes higher-order radial coefficients, k_4, k_5, and k_6 , and we used the CALIB_RATIONAL_MODEL flag provided by OpenCV.

Chessboard images are photos of a patterned board with intersecting horizontal and vertical lines used for camera calibration, as seen in Figure 1. These images, containing different numbers of intersections, were captured at various distances, angles, and positions in the same experimental environment. These images were processed to estimate the focal length, camera translation position, rotation angle, and lens distortion coefficients. Based on these estimated parameters, the distorted chessboard images were corrected using the initUndistortRectifyMap and remap functions in OpenCV.

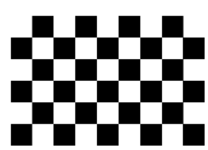

Figure 1. 8×5 chessboard used to estimate the lens distortion coefficient

To measure the lens distortion correction error, we calculated the difference between the intersection coordinates of the corrected chessboard image and the intersection coordinates of the chessboard generated by translating and rotating the original chessboard image. First, we apply the OpenCV calibrateCamera function to the chessboard image data captured by the camera to obtain the tvec and rvec values of the translated and rotated original chessboard image. Furthermore, we obtain the lens distortion coefficients output from the same function and use them to correct the distortion of the chessboard image. Finally, we apply the projectPoints function to the original chessboard image data and the tvec and rvec values obtained above to generate a distortion-free chessboard image data projected to the captured camera position. In other words, the latter is considered an ideal chessboard image without lens distortion. The root mean square (RMS) error, err_{corr} of the differences in the coordinates of all intersection points of the two chessboards in Equation (4), is used as a performance indicator of lens distortion correction. [14] Here, x_i is the coordinate of the intersection point in the corrected chessboard image, $x_i^{projected}$ is the coordinate of the intersection point in the virtual chessboard image projected onto the estimated camera position with the original chessboard image, and N is the total number of chessboard intersection points.

$$err_{corr} = \sqrt{\frac{1}{N}\sum_N\left(x_i - x_i^{projected}\right)^2} \quad (4)$$

3. A proposed lens distortion correction method optimized for the image region

Existing methods estimate lens distortion coefficients using photos where the chessboard pattern spans the entire camera image. This is a global correction method that corrects lens distortion across the entire image. In contrast, the method proposed in this paper divides the entire camera image into four quadrants and estimates lens distortion coefficients optimized for each region using only the chessboard images in a specific quadrant. Furthermore, these lens distortion coefficients are used to correct the chessboard images in the specific quadrants, resulting in an optimally lens-corrected chessboard image. This method is highly effective in real-world applications where the target image is located in a specific region of the camera image, or when only a specific region of the entire image needs to be accurately corrected.

For camera-captured chessboard images, lens distortion coefficients were calculated using both global and regional correction techniques. Each coefficient was applied to correct lens distortion, and the root mean square error was measured. For local correction, only photos with chessboards in the first quarter were used to estimate and apply coefficients.

4. Experiments

4.1 Comparison of errors between basic and extended lens distortion models

In this experiment, chessboard images were captured using the HD Camera app on the Samsung Galaxy SM-M336K smartphone. The shooting conditions were a shutter speed of 1/200, ISO 582, exposure compensation (EV) of 0.00, white balance (WB) of Auto, and an F number of 0.34. The image resolution was 4080 × 3060 pixels, and a total of 110 images were captured in PNG format. The overall size of the chessboard was approximately 181.5 × 272 mm, with 8 × 5 internal intersections. The chessboard images were captured from various positions, distances, and angles to ensure that they were evenly distributed throughout the camera image.

Table 1 shows the RMS errors of the internal intersection coordinates between the corrected and the error-free chessboard images for the case of basic and extended lens distortion models. Compared to the basic model, the extended lens distortion model, which uses three additional lens distortion coefficients, showed a performance improvement of approximately 12.4%.

Table 1. Results of RMS error comparison between basic and extended models

	Basic model	Extended model
RMS error [unit: pixel]	*1.7876*	1.5669

4.2 Comparison of lens distortion correction errors according to the number of intersections on a chessboard

In this experiment, the extended lens distortion model was used to estimate the lens distortion coefficients for cases where the number of intersection points of the chessboard is 5×3, 8×5, 10×7, and 13×9, and the correction error was compared using each lens distortion coefficient for the captured 13×9 chessboard image. Table 2 shows the RMS errors for each case, and it can be seen that there is almost no difference in the accuracy of the lens distortion coefficient estimation or image correction depending on the number of intersection points of the chessboard.

Table 2. RMS result according to the number of intersections

	5 x 3	8 x 5	10 x 7	13 x 9
RMS error [unit: pixel]	*1.5015*	1.4577	1.5060	1.4294

4.3 Comparison of lens distortion correction errors according to shooting distance

This experiment captured 30 images of a 13×9 chessboard at distances of 50 cm, 75 cm, and 100 cm, estimating and correcting the lens distortion coefficients for each image and obtaining the root mean square (RMS) error. Table 3 shows that, when captured from relatively close ranges, the lens distortion coefficient estimation and correction errors are nearly identical across distances.

Table 3. RMS result according to distance

	50cm	75cm	100cm
RMS error [unit: pixel]	*1.4623*	1.4722	1.4846

4.4 Performance Analysis of Local Lens Distortion Correction Methods

To ensure objectivity, the experiments were conducted using two types of mobile devices. The first test was conducted using the Galaxy SM-M336K, and the second test used the Galaxy SM-A516N. The shooting conditions were the same as in Section 1. For global correction, 66 images were captured, with chessboard images distributed across the entire camera image. For regional correction, 66 images were captured, with chessboard images within the first quadrant of the entire camera image. Furthermore, to verify the performance of the proposed method, the RMS error of the internal intersections for the chessboard images in the first quadrant is compared for the global and regional lens distortion coefficients estimated individually.

The second test used the same conditions as the first test, with 38 images each for the global and regional lens distortion coefficient estimation and correction methods.

Figure 2 visually demonstrates the variance in lens distortion coefficient estimation and lens distortion correction performance. Ten randomly selected chessboard images were used, and the root mean square (RMS) error was calculated ten times. The solid line represents the lens distortion coefficient estimate when the chessboard is present in the entire image, while the dotted line represents the estimation using only the chessboard image in the first quarter. Furthermore, the absence of a mark indicates correction for the chessboard image present in the entire image, while the triangular mark indicates correction for the chessboard image present in only the first quarter.

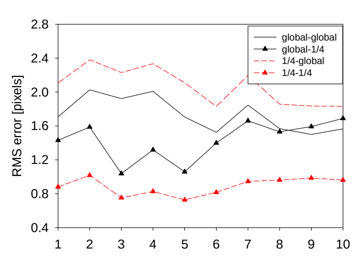

Figure 2. RMS results based on global and regional images with Galaxy SM-M336K

Table 4. RMS error based on global and regional images

Smartphone	SM-M336K				SM-A516N			
	global distortion estimation		regional distortion estimation		global distortion estimation		regional distortion estimation	
	global image	1/4 quad. image	global image	1/4 quad. image	global image	1/4 quad. image	global image	1/4 quad. image
RMS error [unit: pixel]	*1.7373*	1.4303	2.0707	0.8876	1.5351	0.8485	1.8473	0.6873

In all cases, the proposed regional lens distortion coefficient estimation and correction of the chessboard image in the first quarter using the coefficients yielded the smallest error. This performance was significantly superior to the existing global lens distortion correction (global-1/4). Furthermore, as expected, the correction of the chessboard image in the full camera image using local lens distortion coefficient estimates performed the worst. Because the distortion coefficients were estimated for only a portion of the lens, the entire image was not properly corrected. Therefore, when applying the new lens correction method proposed in this paper, it is necessary to define the target region to be corrected from the beginning.

Table 4 shows the experimental results for two smartphone cameras. The average RMS error for the conventional method was 1.14, while the average RMS error for the proposed local lens distortion coefficient estimation method was 0.79, demonstrating a performance improvement of approximately 30%.

Figure 3 shows a portion of a chessboard image where lens distortion coefficients were estimated and corrected using the conventional and proposed methods on the SM-A516N. At the same point, the conventional method (a) shows an error of more than 1.41 pixels relative to the intersection point without lens distortion, while the proposed method (b) shows a significant reduction in the error to 0 pixels.

(a) **(b)**

Figure 3. Lens correction errors for global and regional distortion coefficients in chessboard images (a) regional correction with global distortion coefficients, (b) regional correction with regional distortion coefficients

5. Conclusion

Accurately estimating the image distortion inherent in camera lenses and correcting captured images to approximate the original image are essential in the field of computer vision. This is particularly important in applications such as autonomous driving and mobile robots, where position and distance are estimated using camera images, making accurate correction of camera lens distortion crucial. Because commonly used camera lenses are often small and inexpensive, lens distortion significantly affects the two-dimensional coordinate position of the image.

In this paper, we propose a novel method that divides the entire camera image into four quadrants and estimates lens distortion coefficients optimized for each region using only the chessboard images in a specific quadrant. These lens distortion coefficients are used to correct the chessboard images in the specific quadrants.

We conducted various experiments on methods for measuring lens distortion coefficients and analyzed the results. These results can be used as a reference for estimating lens distortion coefficients. Unlike existing methods that estimate and correct lens distortion coefficients for the entire image area, this paper proposes a method that estimates and corrects lens distortion coefficients for specific regions of the image and demonstrates its improved effectiveness. Therefore, our method is expected to be effectively utilized in a variety of future applications that require high correction accuracy.

For further work, mathematical modeling and analysis of the regional lens distortion coefficients estimation and correction method proposed in this paper should be studied, and research on the optimal regional segmentation method and performance analysis should be conducted.

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References

[1] T.Y. Park, J.Y. Chu, T.W. Seo, and J.T. Oh, “A study on Technology for Global Coordinate Estimation of Camera using QR Code”, *The Journal of The Institute of Internet, Broadcasting and Communication(JIIBC),* Vol. 25, No. 2, pp. 87-93, Apr. 2025. DOI: https://doi.org/10.7236/JIIBC.2025.25.2.87

[2] D. Brown, “Decentering Distortion of Lenses”, *Photogrammetric Engineering*, Vol. 32, No. 3, pp. 444-462, 1996.

[3] Y.J. Zhang, *3-D Computer Vision*, Springer, pp. 44, 2023.

[4] R. Horaud and F. Dornaika, “Hand-eye Calibration”, *The International Journal of Robotics Research*, Vol. 14, No. 3, pp. 195-210, 1995.

[5] A. Kaehler and G. Bradski, *Learning OpenCV 3*, O’Reilly, pp. 644, 2017.

[6] X. Li, B. Zhang, P.V. Sander, and J. Liao, “Blind Geometric Distortion Correction on Images Through Deep Learning”, in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR),* pp. 4855-4864, June 16-20, 2019.

[7] D.S.Cedres, L.Gomez, M.A.Flores, A.Salgado, J.Esclarin, L.Mazorra, and L.Alvarez, “Invertibility and Estimation of Two-parameter Polynomial and Division Lens Distortion Models”, *SIAM Journal on Imaging Sciences*, Vol. 8, No. 3, pp. 1574-1606, 2015. https://doi.org/10.1137/151006044

[8] W. Xian, A. Bozic, N. Snavely, and C. Lassner, “Neural Lens Modeling”, in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR),* pp. 8435-8445, June 18-22, 2023.

[9] B. Huang and S. Zou, “A New Camera Calibration Technique for Serious Distortion”, *Process*, Vol. 10, No. 3, pp. 488-501, 2022. DOI: https://doi.org/10.3390/pr10030488

[10] J. Yeo, N.D. Loh, R. Paniagua-Dominguez, and A.I. Kuznetsov, “EigenCWD: a Spatially Varying Deconvolution Algorithm for Single Metalens Imaging”, *Optics Express*, Vol. 33, No. 13, pp. 28481-28492, 2025. DOI: https://doi.org/10.1364/OE.540831

[11] M. Aleman-Flores, L. Alvarez, L. Gomez, and D. Santana-Cedres, “Automatic Lens Distortion Correction using One-Parameter Division Models”, *Image Processing On Line,* Vol. 4, pp. 327-343, 2014. DOI: https://doi.org/10.5201/ipol.2014.106

[12] J.A. Kang, K.S. Kwon, B.G. Kim, and Y.S. Oh, “A Study on Underwater-Pipe Video Image Mosaicking using Digital Photogrammetry”, *Journal of Korean Association of Geographic Information Studies*, Vol. 11, No. 4, pp. 150-160, 2008.

[13] E. Marchand, H. Uchiyama, and F. Spindler, “Pose Estimation for Augmented Reality: A Hands-on Survey”, *IEEE Transactions on Visualization and Computer Graphics*, Vol. 22, No. 12, pp. 2633-2651, Dec. 2016. DOI: https://10.1109/TVCG.2015.2513408

[14] T. Chai and R. Draxler, “RMSE or MAE? - Arguments against Avoiding RMSE in the Literature”, *Geoscientific Model Development*, Vol. 7, No. 1, pp. 1525-1534, 2014. DOI: https://10.5194/gmd-7-1247-2014