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Lens Distortion Correction of images with Gradient Components

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Abstract

Lens distortions have a significant impact on captured or projected image geometry. This paper proposes a lens distortion correction with gradient components for wide-angle lenses. In most cases, distortion coefficients are estimated using a distortion model by point correspondences. Corrected images using only point correspondences can be compensated excessively, therefore, producing bended lines into the opposite direction near the corners. To curtail these phenomena, we propose to adopt the gradient components in addition to positions to obtain the distortion coefficients. We verified the improved accuracy and the straightness of the proposed method through experimentation.

Keywords : Camera calibration, Lens distortion, Gradient component

I. INTRODUCTION

Geometric lens distortions are typical phenomena in camera images. The most common distortion is radial distortion, which is classified as barrel distortion, pincushion distortion, or a mixture of both types. Radial distortion displaces image points inward or outward from the ideal position. Negative radial displacement is referred to pincushion distortion, whereas positive radial displacement is known as barrel distortion. The camera aperture placed between a lens and an image sensor introduces pincushion distortion. Otherwise, barrel distortion occurs when the aperture is outside of the lens^[1].

Much research on the correction of lens distortion has been conducted in the context of the camera

calibration. Hecht and Zajac^[1] introduced various lens distortions. Tsai^[2] recovered distortion parameters utilizing known corresponding points in 3D space. Weng^[3] extracted distortion parameters by employing calibration objects. These methods are based on distorted image coordinates to calculate distortion parameters using 3D information. Zhang^[4] adopted the planar pattern taken from different orientations. Nonparametric radial distortion models have been proposed in [5].

However, most distortion models employ mapping from the distorted coordinates to the ideal undistorted ones. Therefore they require inverse mapping, or inaccurate approximations. Moreover inverse mappings are time consuming and not practical for real time applications. To eradicate the inverse mapping, Park et al.^[6] proposed a distortion model on undistorted coordinates. In this paper, we adopt this ideal coordinate distortion model to find the distortion coefficients and compensate for the distorted images.

Nonmetric lens distortion correction methods use geometric invariants such as lines^[7-13]. These methods do not need the calibration patterns. Rather,

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they need to extract lines using an edge detection method with a sub-pixel accuracy and edge linking [7-9, 11], Line Support Region (LSR)^[10], plumb-line methods^[12], or a manual selection^[13]. In addition, they optimize the lines using the slopes of lines^[7], a line-fitting^[8-9, 13], a line equation estimation^[10], or estimation of circular arcs^[12]. Finally they optimize the distortion parameters with various methods such as a nonlinear least-squares minimization method (Levenverg-Marquardt)^[7-9], least-squares linear regression^[10], an algebraic approach^[11], the Kukush-Markovskiy-van-Huffel (KMvH) consistent conic fitting method^[12], or a constrained minimization algorithm (modified simplex)^[13]. The main limitations of this class of methods are that straight lines must be obvious in the image.

We propose a lens distortion calibration with gradient components for wide-angle lenses. The compensated images using only point correspondences can be compensated excessively, therefore, resulting in bended lines into the opposite direction near the image corners. To avoid these phenomena, the gradient components of fiducial points are adopted to refine the distortion parameters. Our proposed method employs point grid patterns, therefore, we can extract perpendicular lines from the pattern, which is simple and easy to implement.

This paper is organized as follows. Section II describes distortion models. We present the proposed optimization method with gradient components in Section III. Experimental results and conclusions are described in Section IV and V.

II. DISTORTION CORRECTION MODEL USING IDEAL IMAGE COORDINATES

In this section we describe the radial distortion model using ideal image coordinates^[6]. Theoretically radial distortion is symmetric to the optical axis. We assume that the principal point, where the optical axis intersects the image plane, is the center of radial

distortion^[14]. Then we can model distortion parameters using the distance from the distortion center of a distorted image.

Let (X_d, Y_d) be distorted image coordinates, (X_u, Y_u) be ideal undistorted image position, and (D_x, D_y) be distortion defined by the following equation (1). Distortion is obtained by subtracting the distorted image position from the ideal,

$$\begin{bmatrix} D_x \\ D_y \end{bmatrix} = \begin{bmatrix} X_u \\ Y_u \end{bmatrix} - \begin{bmatrix} X_d \\ Y_d \end{bmatrix} \quad (1)$$

where the principal point is $(0, 0)$. Each position distortion is calculated by subtracting the distorted image coordinates from the ideal undistorted image position.

Let the quadric and quartic distortion coefficients on ideal coordinates be k_{u_1} , and k_{u_2} . Then distortion modeling is defined as (2)^[6],

$$-\begin{bmatrix} D_x \\ D_y \end{bmatrix} = (R_u^2 k_{u_1} + R_u^4 k_{u_2}) \begin{bmatrix} X_u \\ Y_u \end{bmatrix} \quad (2)$$

where $R_u = \sqrt{X_u^2 + Y_u^2}$, This modeling does not need inverse mapping which is time consuming and is not practical for real time application.

Since each data point provides two equations, we have $2N$ equations where N is the number of pattern features. Since there are two unknown parameters and the equations are linear, we can obtain a minimum mean square solution using pseudoinverse as the following equation(3):

$$\mathbf{K}_u = -(\mathbf{Y}^T \mathbf{Y})^{-1} \mathbf{Y}^T \mathbf{D} \quad (3)$$

where

$$\mathbf{D} = \begin{bmatrix} D_x \\ D_y \end{bmatrix}, \quad \mathbf{Y} = \begin{bmatrix} X_u R_u^2 & X_u R_u^4 \\ Y_u R_u^2 & Y_u R_u^4 \end{bmatrix}, \quad \text{and} \quad \mathbf{K}_u = \begin{bmatrix} k_{u_1} \\ k_{u_2} \end{bmatrix}$$

The dimensions of \mathbf{D} and \mathbf{Y} are $2N \times 1$ and $2N \times 2$, respectively.

III. OPTIMIZATION OF DISTORTION COEFFICIENTS

When we compensate for the distortion using the above distortion model, the errors exist between the ideal coordinates and the compensated coordinates. To minimize these errors between the corrected and the ideal coordinates, we propose to optimize the coefficients. Position optimization makes the gradient errors prominent. Actually the corrected points using only position optimization can be compensated excessively, therefore, lines are bended near the image boundaries. To compensate for it, the gradient component must be included.

3.1. OPTIMIZATION WITH POSITION DATA

To minimize the error between the compensated and ideal positions, we optimize distortion parameters \mathbf{P} using the Nelder-Mead simplex method^[15], where \mathbf{P} is the distortion parameters, $\mathbf{P} = (K_{u_1}, K_{u_2}, X_0, Y_0, \theta)$. The distortion parameters to be estimated consist of distortion coefficients K_{u_1}, K_{u_2} , principal point (X_0, Y_0) , and rotation angle θ . The Nelder-Mead simplex method uses multidimensional unconstrained nonlinear minimization. We can find the parameters minimizing the norm between the ideal and distortion compensated positions. The objective function is represented by equation (4):

$$\arg \min_{\mathbf{P}} \|\mathbf{C}(\mathbf{P}) - \mathbf{U}\| \quad (4)$$

where the position vector $\mathbf{C} = [X_c \ Y_c]^T$ represents compensated points, and $\mathbf{U} = [X_u \ Y_u]^T$ denotes undistorted ideal points.

3.2 OPTIMIZATION WITH GRADIENT COMPONENTS

The corrected images using point correspondences between the distorted image and the undistorted points can be compensated excessively, therefore,

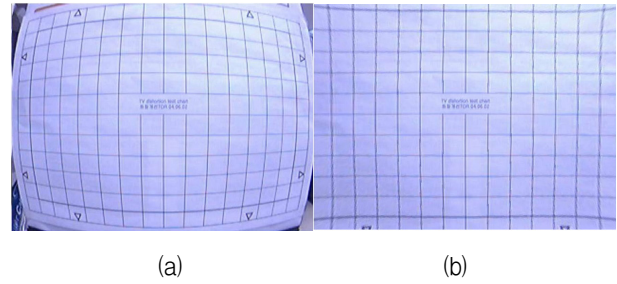


Fig. 1. Distorted image (a), and the compensated image using the position only (b).

leading the images to be bent near the corners as shown in Figure 1 (b).

To avoid these phenomena, the gradient of the boundaries must be included, then minimized to optimize the distortion coefficients \mathbf{P} using Nelder-Mead simplex, as the following equation (5):

$$\arg \min_{\mathbf{P}} \left(\sum_i \left\| \frac{\partial v_i(\mathbf{P})}{\partial y} \right\| + \sum_j \left\| \frac{\partial h_j(\mathbf{P})}{\partial x} \right\| \right) \quad (5)$$

where v_i and h_j are the vertical line and the horizontal line, respectively, $\|\partial v_i(\mathbf{P})/\partial y\|$ is the vertical gradient component, and $\|\partial h_j(\mathbf{P})/\partial x\|$ means the horizontal gradient component.

In Figure 2 (b), the inclusion of gradient components makes the corners straight. Finally the objective function of distortion coefficients that considers both position and the gradient components is defined as follows:

$$\arg \min_{\mathbf{P}} \left\{ \|\mathbf{C}(\mathbf{P}) - \mathbf{U}\| + \alpha \left(\sum_i \left\| \frac{\partial v_i(\mathbf{P})}{\partial x} \right\| + \sum_j \left\| \frac{\partial h_j(\mathbf{P})}{\partial y} \right\| \right) \right\} \quad (6)$$

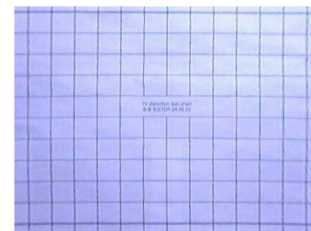


Fig. 2. Compensated image using both gradient components and position

where α is the weighting factor. In our experiments, we set α to 100.

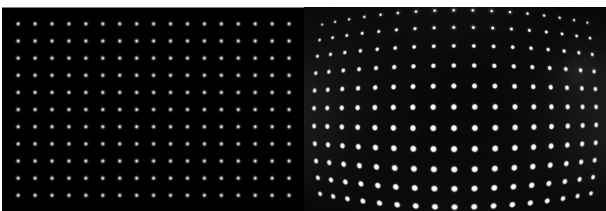
IV. EXPERIMENTAL RESULTS

We used the Canon 40D camera with Canon EF 15mm f/2.8 fish eye lens. We employed 2D Gaussian circles as fiducial points, and apply correlation to detect the position automatically.

After extracting the feature position, the distortion coefficients are calculated using equation (3). The compensated images are obtained using the optimized distortion coefficients by the proposed method.

Distortion correction error is summarized in Table I. The RMS (Root Mean Square) error between image coordinates and the ideal coordinates is 23.01 pixels, and maximum error is 107.66 pixels before correction. After compensation using proposed distortion parameters, the RMS error is decreased to around 1 pixel. From the table, we verify that the RMS error of our proposed method is less than the Alvarez *et al.* method^[11]. Alvarez *et al.* method is an algebraic approach to the estimation of the lens distortion parameter based on the rectification of lines in the image. They provide an online demonstration and exploits user assistance in identifying points on straight lines. We test the distorted pattern image as shown in Figure 3., and selected the same number of points to compare our method with their method.

The experimental results of distorted and compensated images are shown in Figure 4. We verify that the proposed method restores the distortion of real



(a) (b)

Fig. 3. Gaussian feature pattern (a), and the distorted feature image (b).



Fig. 4. Distorted images (left column) and compensated images (right column).

Table 1. Distortion correction errors.

Method	RMS ERROR	MAX ERROR
Before correction	23.01	107.66
Position correction	2.41	14.09
Proposed method	1.10	4.54
Alvarez <i>et al.</i> method [11]	2.05	9.37

images, resulting in natural looking images without excessive compensation.

V. CONCLUSION

We propose a lens distortion calibration method with gradient components. The corrected images using only point correspondences can be compensated excessively, leading the images to be bent near the corners. To curtail these phenomena, we propose to add the gradient components in addition to position error to estimate the distortion coefficients. We verified the accuracy and the straightness of the proposed method through experimentation. The proposed method can compensate for the extremely distorted images in a simple and efficient manner.

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