Intrinsic parameter estimation of a fish-eye camera using trajectories of feature points when rotating the camera

Yuki Tanaka*1, Gakuto Masuyama*2, Kazunori Umeda*2
*1 Graduate School of Science and Engineering, Chuo University
1-13-27 Kasuga, Bunkyo-ku, Tokyo, 112-8551 Japan
*2 Faculty of Science and Engineering, Chuo University
1-13-27 Kasuga, Bunkyo-ku, Tokyo, 112-8551 Japan

We propose a simple method to estimate fish-eye camera's intrinsic parameters without calibration targets. Our method takes advantage of trajectories of feature points in the scene. The trajectories of feature points are obtained by a rotation movement of the camera in a horizontal plane. We therefore can utilize rich feature points for calibration, and furthermore, specific calibration targets are not required. The validity of proposed method is verified by simulation experiments using artificial data.

1 Introduction

While a fish-eye camera has a very wide angle, images taken by this camera have a large distortion. It is important to determine intrinsic parameters for accurate perspective projection transformation of this image or measurement using a fish-eye camera. Most of the previous studies which estimate fish-eye camera's intrinsic parameters require specific calibration targets [1]. Therefore, it is supposed that results of the estimation vary by difference of obtained images. We propose estimation method of fish-eye camera's intrinsic parameters without calibration targets. Our method uses information of feature point trajectories when rotating the camera (See Fig. 1). Therefore, proposed calibration method can be implemented easily. This method enable easy calibration. This paper shows results of simulation experiments and verify availability of this method.

2 Model of a fish-eye camera

This section explains intrinsic parameters and a model of a fish-eye camera.

2.1 Intrinsic parameters

A projection model of a fish-eye lens is generally represented by an angle θ [rad] and an image height r [pixel]: θ represents an angle between projection line from a scene to the lens and a optical axis of the lens; r represents the distance projected point and optical axis. This paper uses a following model [2]

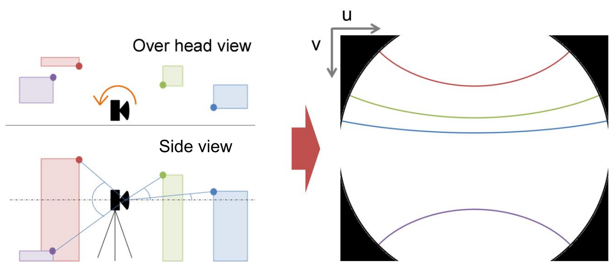

Fig. 1 Making feature point trajectories

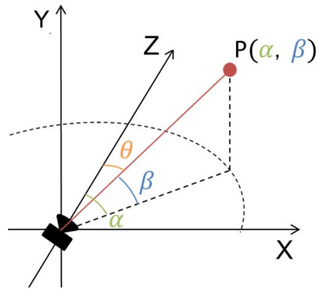

Fig. 2 3D point

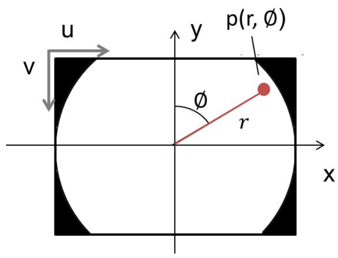

Fig. 3 Projected point

$$r \approx k_1\theta + k_3\theta^3 + k_5\theta^5. \tag{1}$$

Therefore, intrinsic parameters are $\mathbf{I} = [k_1\ k_3\ k_5\ c_u\ c_v]^T$, which includes image center c_u, c_v.

2.2 Projection of a 3D point to an image

3D point P is represented by azimuthal angle α [rad] and elevation angle β [rad] (see Fig. 2). The angle θ is then represented as

$$\theta = \arccos(\cos\alpha \cdot \cos\beta). \tag{2}$$

ϕ [rad] is an angle between y axis and a line from the image center to projected point p as depicted in Fig. 3:

$$\phi = \arctan\left(\frac{\sin\alpha}{\tan\beta}\right). \tag{3}$$

Projected point $p(r,\phi)$ is converted to orthogonal coordinates $p(u,v)$, where

$$u = r\cos\left(\frac{\pi}{2} - \phi\right) + c_u, \tag{4}$$

$$v = -r\sin\left(\frac{\pi}{2} - \phi\right) + c_v. \tag{5}$$

The center of uv coordinates system is upper-left corner of the image.

3 Estimation method of intrinsic parameters

This section explains proposed estimation method of intrinsic parameters. The flow of this method is shown in Fig. 4.

In (a) of Fig. 4, image center c_u, c_v are estimated. Feature point trajectories obtained from rotation of camera are symmetric (see Fig. 1). Thus, image center c_u, c_v are estimated by this symmetric shape.

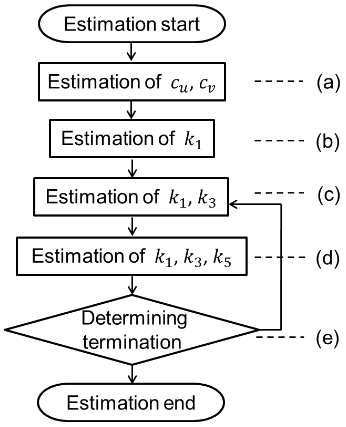

Fig. 4 Estimation flow

In (b)-(d) of Fig. 4, we estimate optimal k_1, k_3, k_5, which minimize evaluation function D. The evaluation function D is defined as following:

$$D_{r_j} = \sum_{i=1}^{N} |\mathbf{m}_{\mathbf{f_i}} - \mathbf{m}_{\mathbf{r_i}}|, \tag{6}$$

$$D_{s_j} = \sum_{i=1}^{N} ||\mathbf{m}_{\mathbf{f_1}} - \mathbf{m}_{\mathbf{r_1}}| - |\mathbf{m}_{\mathbf{f_i}} - \mathbf{m}_{\mathbf{r_i}}||, \tag{7}$$

$$D = \sum_{j=1}^{M} (D_{r_j} + D_{sj}), \tag{8}$$

where m_{f_i} is projected point and m_{r_i} is re-projected point. $i = 1$ corresponds to the left end of each trajectories, and $i = N$ corresponds to the right end of each trajectories. N is number of points in one trajectory. M is the number of trajectories. m_{r_i} can be calculated using α, β and $\mathbf{I}$.

α and β are roughly initialized at first. Using the c_u, c_v and α , β, we then estimate k_1, k_3, k_5 by relevant optimization technique. In this paper, we used modified Powell method. α and β are updated by estimated $\mathbf{I}$. Thus, the estimation of k_1, k_3, k_5 and the calculation of α, β is alternated.

4 Simulation experiments

We tested our estimation technique using simulation images. The simulation images were supposed to be obtained from a fish-eye camera rotated by 180 [deg] in a horizontal plane. An Optical axis of the camera were paralleled to the horizontal plane. True values we used to obtain simulation images were shown in Table 1, which was estimated from a real camera by a calibration method in [3]. Each projected points was added artificial noise from uniform distribution in each axis. Maximums of the noise were 0, 0.5, 1, and 2. The image size was 668 [pixel] × 524 [pixel]. Projected points were 2377 points, and $M = 14$. $N = 180$ at most. All initial value of estimation variables were 0.

The results are shown in Table 2. Also, an example of the converged points is shown in Fig. 5. This figure represents trimmed upper-right of the simulation image. These results indicate that estimation by proposed method is approximately correct. If we added no error, re-projection error was no more than 0.5 [pixel] on average. If maximum error we added was 2 [pixel], re-projection error was approximately 1.3 [pixel] on average.

Table 1 Teue values of intrinsic parameters

k_1	k_3	k_5	c_u [pixel]	c_v [pixel]
169.26	12.32	-0.68	340.07	235.95

Table 2 Results of estimation

added error	0 [pixel]	0.5 [pixel]	1 [pixel]	2 [pixel]
k_1	171.34	170.70	169.7	170.64
k_3	10.42	10.61	11.70	9.90
k_5	-0.15	0.05	-0.21	0.52
c_u [pixel]	340.15	340.13	340.11	340.05
c_v [pixel]	235.95	235.94	235.93	235.91
$\sum_{j=1}^{M} D_{r_j}$ [pixel]	1098.68	1071.20	1561.86	3136.09
$\sum_{j=1}^{M} D_{s_j}$ [pixel]	755.29	725.19	1126.18	6054.21
D [pixel]	1854.97	1796.39	2688.04	9190.3

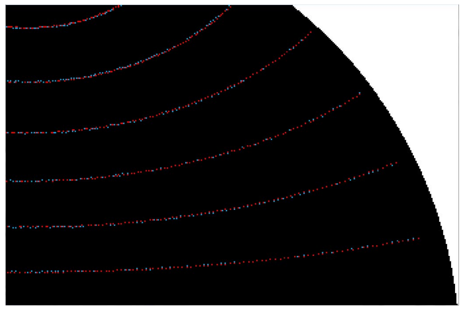

Fig. 5 Estimation result when maximum added error is 0.5 [pixel]. Blue dots are projected points and red dots are re-projected points.

5 Conclusion

We proposed a method to estimate fish-eye camera's intrinsic parameters without calibration targets. Our proposed method used trajectories of feature points when the camera rotated on the horizontal surface. The simulation experiments demonstrated that our method could estimate correct value approximately. In the feature, we improve precision of this method by reforming the flow of estimation.

References

[1] D. Scaramuzza, A. Martinelli and R. Siegwart, "A Toolbox for Easily Calibrating Omnidirectional Cameras," Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2006), pp. 5695-5701, 2006.

[2] J. Kannala and S. Brandt, "A generic camera model and calibration method for conventional, wide-angle, and fish-eye lenses," IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol. 28, No. 8, pp. 1335-1340, 2006.

[3] R. Okutsu, K. Terabatashi, U. Umeda, "Calibration of Intrinsic Parameters of Fish-Eye Camera Using a Sphere," IEICE TRANSACTIONS on Information and Systems D, Vol. J93-D, No. 12, pp. 2645-2653, Dec. 2010 (in Japanese).