Camera parameters estimation for 3D-Based Synthesis and 3D Reconstruction

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Abstract

In this paper, we propose a new camera calibration method for the 3D-based image synthesis and 3D reconstruction. We improve the problem as changing the principle point for obtaining the linear equation. According to the error rate, we adapt the non-linear method that minimizes the intrinsic parameters. Namely, it minimizes the intrinsic parameters error with maintaining the computational conciseness. As a result, we can find optimized camera intrinsic parameters and adapt to image synthesis and reconstruction. .

Keywords--- **Camera Calibration, 3D-based image synthesis, 3D Reconstruction**.

1. Introduction

One of the main research fields in computer vision is the matching of stereoscopic images. This matching enables the building up of a 3D surface of the scene. Camera calibration is the fundamental task for the 3D-based synthesis and 3D reconstruction from the correspondences. It is divided into two methods roughly. One is the using auto calibration method and the other is using 3D data such as the pattern information. The former is more progressive method, because there is no constraint or previous information of the scenes. Therefore, auto-calibration method has a difficult progress dealing with the complicated non-linear equations. By reason of this, it gives some restricted condition on the intrinsic camera parameters in recent researches. In this case, we can solve the linear equations instead of complicated non-linear equations. Auto-calibration is the computation of camera internal calibration and/or metric properties of the scene from a set of uncalibrated images. [1][2][3][4] The original auto-calibration method based on kruppa's equations was restricted to cameras with fixed internal parameters, and early work in this area maintained this restriction. However, this constraint occur the error to the camera intrinsic parameters. We present a simple approach to auto-calibration for the purpose of reducing the error. We formulate a constraint in terms of the variable principle points and improve the problem as changing the principle point for obtaining the linear equation. According to the error rate, we adapt the non-linear method that minimizes the intrinsic parameters. Namely, it minimizes the intrinsic parameters error with maintaining the computational conciseness. Experimental results show the performance of the proposed method is better than the previous. We also demonstrate examples of the 3D-based image synthesis and the 3D reconstruction.

3. Proposed Calibration Approach

General camera calibration methods for inducing the linear equations can generate the errors instead of reducing the computation costs by enforcing the strong constraint. [1][2][3][4][8] We improve the problem as changing the principle point for obtaining the linear equation. According to the error rate, we adapt the non-linear method that minimizes the intrinsic parameters error. Namely, it minimizes the intrinsic parameters error with maintaining the computational conciseness. Generally, it is assumed that the skew and principle points are zero.[10][11] This disregards an error by the camera distortion. Our proposed method is represented that minimizes the error differs in each camera.
Camera parameters can be recovered from uncalibrated images in the following stages.

1. Set the matrix C for varying the principle points

$$P' = CP, \quad C = \begin{bmatrix} 1 & 0 & -o_{xi} \\ 0 & 1 & -o_{yi} \\ 0 & 0 & 1 \end{bmatrix}, \quad \begin{matrix} -d \le o_{xi} \le d \\ -d \le o_{yi} \le d \end{matrix}$$

2. Compute the absolute dual quadric Ω [8][10]

$$(P'^{(1)} Q_\infty^* P'^{(2)^T}) = 0$$
$$(P'^{(1)} Q_\infty^* P'^{(3)^T}) = 0$$
$$(P'^{(2)} Q_\infty^* P'^{(3)^T}) = 0$$
$$(P'^{(1)} Q_\infty^* P'^{(1)^T}) = (P'^{(2)} Q_\infty^* P'^{(2)^T})$$

3. Decision the error rate from the Error Function E

	Previous Method	Proposed Method
Focal Length	206.72	190.421
Skew	0.121	0.111
Principle Point (u_0, v_0)	(0.541 , 0.053)	(0.499 , 0.042)

$$\mathbf{E}(\mathbf{o}_x, \mathbf{o}_y) = \sum_{i=1}^{n} \left\| \mathbf{P}_i \mathbf{Q}^*_\infty \mathbf{P}_i^{\mathbf{T}} - D(\mathbf{P}_i \mathbf{Q}^*_\infty \mathbf{P}_i^{\mathbf{T}}) \right\|_F$$

4. Experimental Result

Experimental results show the good matching result with a subpixel error. It is more efficient matching method in images sequence with a small motion. It has found the more correspondence with a small error. Figure.6 shows the feature points found 1803 points in figure 5(a), 1951 points in figure (b), 2019 points in figure (c), 2163 points in figure (d).

Table 1. Experimental results of the figure 2

Image	Image size(pixel)	corresponding Points	Geometric error (pixel)
(a)	640×480	513	0.317
(b)	640×480	501	0.298
(c)	720×480	524	0.382
(d)	720×480	695	0.394

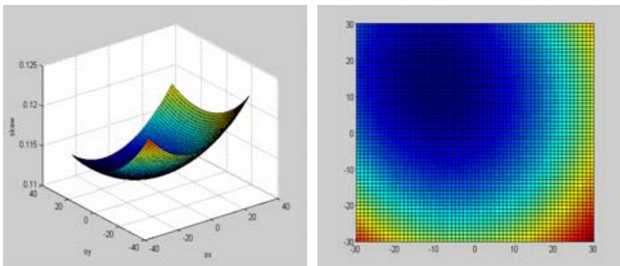

Figure 2. skew values as changing (ox_i, oy_i)

We measured the intrinsic parameters error as changing the o_{xi}, o_{yi} from -30 to 30 by the propose method. As shown in figure 5 and 6, the intrinsic parameters converge on the some area.

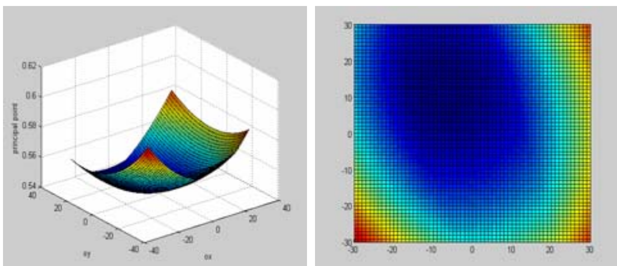

Figure 3. Principle Points as changing (ox_i, oy_i)

It found the intrinsic parameters at the principle point (-7,13) with a minimum error computed from the proposed error function. The table 2. represents camera parameters found in images and shows more accuracy than the previous method.

Table 2.Comparing with the previous method

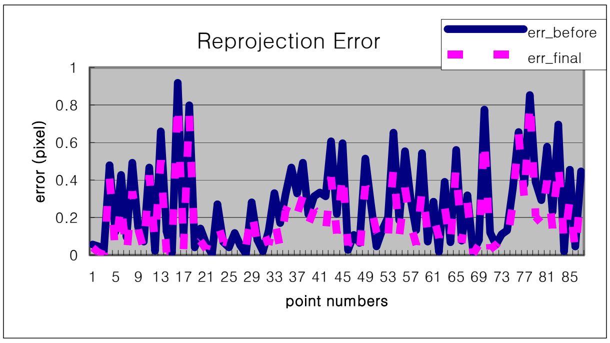

Figure 4.Reprojection error

$$err_{reprojection} = \sqrt{(x_i - x_i^{'})^2 + (y_i - y_i^{'})^2}$$

Figure.4 shows the reprojection error comparing with the previous method. And Table 3. shows the average of reprojectin error.

Table 3.Comparing with the previous method

Avg. of Reprojection error	Previous method	Proposed method
(pixel)	0.2677	0.1993

5. Conclusions

In this paper, we have presented a camera calibration method of image sequences based on the projective factorization which is improved by the error minimization method.[11] It is possible that the principle points are changed during the calibration process. Basically, it need not to induce the complicated equations and minimizes the intrinsic parameters error with maintaining the computational conciseness. Our experiments show that the proposed approach allows obtaining the robust estimates of camera intrinsic parameters in a computational simple way that can be easily implemented in practice. We also demonstrate examples of the 3D-based image synthesis and 3D reconstruction from uncalibrated images.[13][14]

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Figure 7. Input Images

Figure 9. Input Images

Figure 8. Synthesis of the 3D model

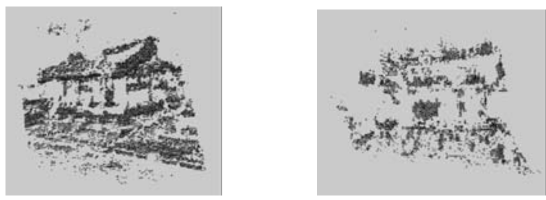

Figure 10. 3D Reconstruction