POSE ESTIMATION FROM LINES BASED ON THE DUAL-NUMBER METHODS

Caixia Zhang [1], Zhanyi Hu [2] and Fengmei Sun [3]
[1 3] Institute of Image Processing and Pattern Recognition, North China University of Technology Beijing 100041, P.R. China

[2] National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences Beijing 100080, P.R. China

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Abstract: It is a classical problem to estimate the camera pose from a calibrated image of 3D entities (points or lines) in computer vision. According to the coplanarity of the corresponding image line and space line, a new group of constraints is introduced based on the dual-number methods. Different from the existing methods based on lines, we do not use an isolated point on either the space line or the image line, but the whole line data. Thus, it is evitable to detect the corner as well as the corresponding propagating error.

1 INTRODUCTION

Estimating the camera pose from a calibrated image of 3D entities with known location in the space is an important issue in computer vision. When the entities are points, the corresponding problem is usually called as the PNP (perspective-n-point) one, while they are lines, called as the PNL (perspective-n-line) one. Although lines provide a more stable image feature to match and the point feature often will be missing from consecutive image for carrying on a series of camera pose determination, So far, the former have been extensively studied, e.g. (Fishler, M., 1981-Fiore, P., 2001) to cite a few, while the latter only by few researchers, e.g. (Kumar, R., 1994- Ansar, A., 2003). The possible reason why the PNL problem is not extensively paid attention like the PNP one is that line representions are very awkward in 3-space (Hartley, R., 2000) and it is obscure to transform them between different coordinate frames. In this paper, in virtue of the dual number methods, the PNL problem is revisited.

The existing methods based on lines include Kumar, (R., Hanson, A., 1994, Ansar, A., 2003 and Liu, Y., 1990). In the above methods, it is inevitable to use the isolate point on the space line or the image line. However, we don't know which one should be selected and their effect on the results. So, we propose a new algorithm for pose estimation from lines only which can be looked as the extension of Lu's work based on points (Lu, C., 2000.), that is, we don't use a single point on either the space line or the image line, but the whole line which can be determined by all points on it. According to the coplanarity of the corresponding image line and space line that is represented by a unique dual vector, a new group of constraints is introduced.

This paper is organized as follows: Section 2 introduces some concepts of the dual number method, line coordinate transformation as well as the relation with the well-known rigid transformation. Section 3 describes the basic constraints from lines and the orthogonal iteration algorithm. Section 4 provides the experiment results, both computer simulation and real data are used to validate the proposed technique and compare our method to existing ones. Finally, some concluding remarks are given in section5.

2 PRELIMINARIES

Some mathematical terms are introduced at first.

2.1 Dual Number and Dual Angle

The following definitions are from (Fischer, I., 1999).

Definition 1: A dual number, which perhaps should be called a "duplex" number in analogy with complex number, is written as $\hat{a} = a + \varepsilon a^*$. Where $\varepsilon \neq 0, \varepsilon^2 = 0$, symbol a and a^* represent

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the primary (or real) part and the dual component of duplex (or dual) number respectively.

Definition 2: The dual angle is defined as

$$\hat{\theta} = \theta + \varepsilon s$$

where θ represents the inclination between two lines and s is the shortest distance between them.

2.2 Representation of Lines

By $\vec{f}$ the direction of a space line L, vector $\vec{r}$ connects origin O to any point on the line L. Denote $\vec{g} = \vec{r} \times \vec{f}$, so L can be determined by a dual vector $\hat{h}$ that is $\vec{f} + \varepsilon\vec{g}$.

2.3 Line Coordinate Transformation

Assume line L is expressed by a dual vector whose form is $\hat{h} = \vec{f} + \varepsilon\vec{g}$, the dual angle $\hat{\theta} = \theta + \varepsilon s$ is coupled with the rotated angle and the translation magnitude along the line L, then from (Fischer, I., 1999), we know that $\hat{h}_C = \hat{T}^C_W(\hat{\theta},\hat{h})\hat{h}_W$

$$T^C_W(\hat{\theta},\hat{h}) = U + \varepsilon V \qquad (1)$$

where $\hat{h}_W$ and $\hat{h}_C$ are different representations of the same line in the world frame {W} and in the camera frame {C} respectively, U and V can be determined by $\vec{f},\vec{g},\theta,s$. Note that U is a rotation matrix, and $UV^\tau + VU^\tau = 0$, so (U,V) have total 6 degrees of freedom.

2.4 The Orthogonal Projection of a Line on a Plane

We consider only the plane passing through the origin of the frame, that is, plane $\prod$ owns the following special form: $aX + bY + cZ = 0$,
where $a^2 + b^2 + c^2 = 1$.

Let line L be expressed by a dual vector in the form $\hat{h} = \vec{f} + \varepsilon\vec{g}$, then the projection line L_p of L on the plane $\prod$ is expressed in the form:

$$\hat{h}_p = \lambda(N \cdot \vec{f} + \varepsilon N^* \cdot \vec{g})$$

where $N = \begin{pmatrix} b^2 + c^2 & -ab & -ac \\ -ab & a^2 + c^2 & -bc \\ -ac & -bc & a^2 + b^2 \end{pmatrix}$, N^* is the transpose of the adjoint of N , λ the scale factor.

3 THE MAIN CONSTRAINTS AND THE ALGORITHM

In this paper, we assume the camera parameters including lens distortion are known.

3.1 The Main Constraints

After discarding the lens distortion, the camera model is looked as the pinhole one. Let l be the projection of line L on the normalized image plane which is one with $z = 1$ in the camera frame, $\prod_l$ the plane passing through the optical center O and line l . Line L is expressed by the dual vector $\hat{h}_W$ in the form $\hat{h}_W = \vec{f}_W + \varepsilon\vec{g}_W$ in the world frame and by $\hat{h}_C$ in the camera frame.

If the equation of the image line l in the image plane is $ax + by + c = 0$, then the equation of $\prod_l$ in the camera frame is $aX_C + bY_C + cZ_C = 0$.
Under the idealized model, line L should be on plane $\prod_l$, that is, the projection of L on plane $\prod_l$ should be overlapped with line L. This fact is expressed by the two following constraints according to the result in Section 2.4:

$$U\vec{f}_W = N \cdot U\vec{f}_W \qquad (2)$$

$$U\vec{g}_W + V\vec{f}_W = N^* \cdot (U\vec{g}_W + V\vec{f}_W) \qquad (3)$$

In fact, three equations in Equ. (2) are linearly dependent each other, while only two equations in Equ. (3) are linearly independent. Thus each line correspondence gives three independent equations in (U,V) .

3.2 The Algorithm

If the internal relation between U and V is neglected, the above equations are linear ones with respect to U and V , particularly, Equ. (2) only involves U , thus, U is solved linearly by SVD, and then substituting it into Equ. (3), V is also solved by the similar method.

However, these can be only used as an initial guess for the optimization scheme because of the existence of noise. Furthermore, we used the similar method to that in (Lu, C., 2000) to compute the rotation matrix firstly iteratively and then the translation vector linearly. The procedure is described as follows:

Step 1. Computing U

Assume that the kth estimation of U is U^k, substituting it into the right of Equ. (2), the right is obtained, Accordingly, the next estimation U^{k+1} is determined by the similar method to that in (Lu, C., 2000).

Step 2. Computing t

After the rotation recovered, substituting the final U into Equ. (3), V can be solved again by SVD. Furthermore, the translation vector can be obtained.

4 EXPERIMENTS

We conduct lots of experiments, both simulation and real data, to test our algorithm and compare to those of (R., Hanson, A., 1994) and(Ansar, A., 2003). These three method are called as new method, KHRT method and AD method respectively.

4.1 Simulation

The relative translation error and rotation error are defined as: $T_{err} = \frac{2\|T_e - T_r\|}{\|T_r\| + \|T_e\|}$, R_{err} = sum of three absolute Euler angles of $R_e^{\tau} R_r$,where the subscripts e and r denote the evaluated and true value.

Assuming the calibration matrix K be

$$K = \begin{bmatrix} 1200 & 0.3 & 256 \\ 0 & 960 & 256 \\ 0 & 0 & 1 \end{bmatrix}$$

Uniformly distributed random 3D rotation is generated for each translation. For the translation, the first two components x and y are selected uniformly in the interval [100,200], while the third component z in the interval [50,600]. The set of 3D space point are produced randomly in the box defined by $[-100,100] \times [-100,100] \times [100,400]$. Two points define a line. Accordingly, an image of size 512×512 is generated. In the following tests, the noise is only added in the image data.

1. Dependence on noise levels

Each image line is perturbed as follows: 50 points are selected randomly on each image line firstly, then a zero mean Gaussian noise with standard deviation from 0 to 5 pixels is added to both coordinates of points independently. Finally, noise is propagated to the line parameters following.

For each noise level, 400 random poses are generated. For each pose, 8 lines are generated. The average rotation error and translation error are computed under each noise level and plotted with varying noise. The plots are shown in Figure 1 and 2.

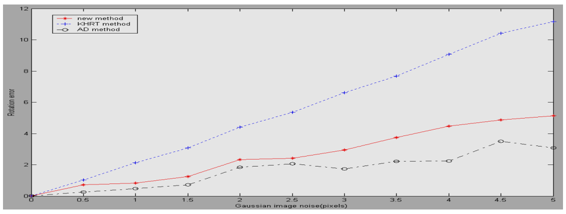

Figure 1: Rotation error varying with noise level.

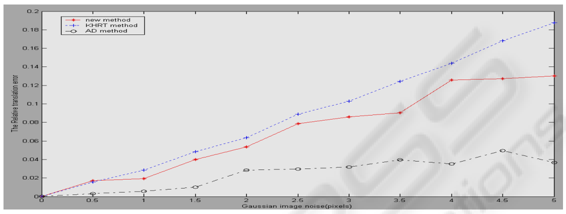

Figure 2: Translation error varying with noise level.

2. Dependence on number of lines

Under the noise level of 1.5 pixel, we showed that the results varying along with the number of lines which is varied from 3 to 15. For each number, we perform 400 times independent experiments. The averaged results are shown in Figure 3 and 4. Besides, AD method outperforms ours slightly under the rotation error. However, for the least 3 lines, AD method can not be used. Hence, using the classic robust algorithm-RANSAC(Fishler, M., 1981), only KHRT method and ours can be considered. It is necessary to note that the result of KHRT method is obtained as the initial guess is assumed to be the ground truth. If the initial guess is not close to the ground truth, the result is not so good. However, for our method, the initial guess can also be obtained under 3 lines. Although it may be far away from the ground truth, our algorithm will often be convergent accurately. When the number of lines goes up to 8, the errors under all three methods tend to be stable.

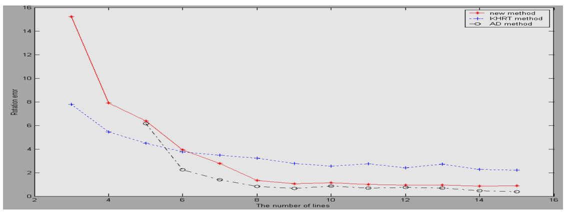

Figure 3: Rotation error varying with the number of lines.

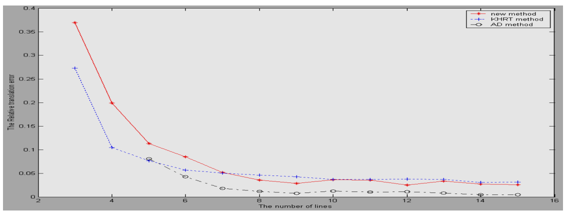

Figure 4: Translation error with the number of lines.

The above two experiments show that our results are worse slightly than those of (Ansar, A., 2003). However, we think it maybe many redundant constraints are added by mathematical operations. We also note that the translation error is much worse than that of (Ansar, A., 2003) especially, it is possible because of the propagated error from the rotation estimation. Moreover, it has been shown that the result of solving rotation and translation simultaneously is better than that of solving them separately (R., Hanson, A., 1994).

4.2 Real Experiments

All images were taken with a Nikon Coolpix990 camera. We take an image of a real box fixing the camera internal parameters. The image resolution is 640*480 pixels. We extract 7 line segments on the box manually, as shown in red in Figure 5. The camera internal parameters are calibrated using the method in (Faugerous, O., 1986). Using the estimated pose, all of the box's edges are reprojected onto the image, the results are shown in Figure 6.

Figure 5: Seven lines on the box.

Figure 6: Reprojection using R,t under seven lines.

5 CONCLUSIONS

In this paper, according to the coplanarity of the corresponding image line and space line, a new group of constraints is introduced based on the dual number. Different from the existing methods based on lines, we do not use an isolated point on either the space line or the image line, but the whole line data. Thus, it is evitable to detect the corner as well as the corresponding propagating error. In addition, the optimization value is searched only in the space of orthogonal matrix, so as compared with other optimization methods, our algorithm may be faster and it seems that it is not necessary to provide better initial value.

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