The Fifth Asian Conference on Computer Vision, Melbourne, Australia, Jan 23-25, 2002

Algebraic Characteristic and Geometric Interpretation of Planar Motions and their Applications to Camera Self-calibration

Le LU
Visual Computing Group
Microsoft Research China
Beijing 100080, P. R. China

Hung-tat Tsui
CVUP Lab, Electronic Engineering Dept.
The Chinese University of Hong Kong
Shatin, NT, Hong Kong

Abstract

Vision tasks with constrained camera motion have been discussed for a long time since Active Vision appeared. As an example, Camera under planar motion can often simplify the works, like camera self-calibration, scene reconstruction and robot self-location. In this paper, we provide detail information on the algebraic characteristic and geometric interpretation of planar motion. It does help to build up a special vision system and make it more feasible for practical use. In this paper, an explicit algebraic analysis of the camera planar motion detection is first given. A special spatial parameterization is used to explain the geometric meaning of planar motions and for the detection of such motions. Three kinds of planar motions: non-collinear, collinear and stationary camera motion, are considered. According to this, we design a practical simplified vision system, which can be easily used for outdoor vision tasks. Lastly, we discuss the stability and uncertainty propagation, while 2D image matching points project onto a 1D virtual camera retina. It is critical for the original image matching uncertainty to be carefully handled to avoid the error blowup due to 2D to 1D projection. Experiments on camera self-calibration and scene reconstruction using simulated data and real images show the validity and effectiveness of our method.

Keywords: Camera Planar Motion, Uncertainty Projection, Camera Self-calibration

1. Introduction

Planar motion of a camera is a useful motion configuration for camera self-calibration and 3D reconstruction. An analysis of critical motion sequences, including planar motions, for uncalibrated Euclidean reconstruction was given by Sturm [2, 3]. Most motion cases of mobile robot self-location problems are planar motions. For active vision systems, planar motion is also widely used. Image-based modeling and rendering are very hot topics in computer vision and graphics society nowadays. Different kinds of planar motions of the camera are used in many applications, such as the work of Shum and Szeliski [5, 6, 7]. All these show that the analysis of planar motion is very necessary and useful in many computer vision and graphics applications.

In Faugeras et al [1], the non-linear problem of self-calibration is simplified to a linear process by using a camera undergoing planar motions and assuming a 1D camera model. This approach avoids the critical convergence problem of the Kruppa equation used by many self-calibration methods [8,9]. However, it also brings some new problems to be solved. These include the detection of planar motions and robust estimation of the 1D trifocal tensors under noises, where the uncertainty of initial 2D image matching may be magnified by the projection of 2D image points to 1D image points. The planar motion detection method used by Faugeras et al in [1] is somewhat complex to be understood and implemented. These motivated us to perform the research reported in this paper. Further more, we shall present an explicit analysis of the visual motion when the camera is under different planar motion configurations. Especially, the 2D visual motion of trifocal lines in different image views is our emphasis.

On the other hand, stratified 3D scene reconstruction, which consists in upgrading a projective reconstruction [10, 11, 12, 13] to Euclidean reconstruction with camera intrinsic parameters information [14, 15, 16], has been realized as an important 3D reconstruction approach. The intrinsic parameters of a camera also play a critical role in scene modeling from concentric mosaics [18]. Camera calibration has significant influence on many object modeling related applications.

The paper is organized as follows. In Section 2, we review the planar motion detection methods proposed in Faugeras et al [1]. An analysis of the algebraic and geometric properties of planar motions is discussed in Section 3. Robust estimation of 1D trifocal tensor under three camera configurations is discussed in Section 4. Method to eliminate the 1D projections with noise magnification is presented in Section 5. Experimental results are presented in Section 6. A summary and a conclusion are given in Section 7.

2. Previous Method on Planar Motion Detection

Planar motion means that the camera moves on a plane, and its rotation axis must be perpendicular to the plane. The plane intersects a line with the retinal plane of camera, which is called the trifocal line [1]. For a planar motion as shown in Fig 1, the camera can have different positions and orientations, and each has an intersecting trifocal line with the motion plane. In a real experiment, we try to make a camera to move in some planar motions. Due to vibration and other mechanical errors, some of the motions may be not be on the same plane with the others. So, we must detect the set of motions on the same plane. The method (**FM**) proposed in Faugeras et al [1] is as follows:

The locus of all points in space that projects onto the same points in two images is the well-known horopter curve. Let **F** be the fundamental matrix and **x** a point in the first image. So we have the epipolar constraint as $x^T Fx = 0$, which is the equation of a conic (c). The matrix of this conic is $G = F + F^T$ since the antisymmetric part of **F** is irrelevant. Note that we have two such identical conics, (c) and (c'), one for each view. From the two view projective geometry, we know that the epipoles **e** and **e'** belong to conics (c) and (c') respectively, so the cubic curve has to go through the optical centers C and C' [4]. The conclusion is that in the case of a rotation with respect to an axis ***L***, the horopter curve (**H**) splits into a line and a circle in the motion plane $\prod$. Its image (c) (respectively (c')) therefore also splits into two lines, the image line ℓ (respectively the line ℓ') of ***L*** and the line ρ (respectively ρ') of the intersection of $\prod$ with the retinal plane. For a set of three views, we consider the plane $\prod_{12}$ corresponding to the first rotation and the plane $\prod_{23}$ corresponding to the second. The motion is planar if and only if the two planes $\prod_{12}$ and $\prod_{23}$ coincide with the trifocal plane. This gives a test for the planarity of a motion. The three fundamental matrices yield the three trifocal lines ℓ_i represented by $t_i = e_{ij} \times e_{ik}\ i = 1,2,3, i \neq j \neq k$. The three matrices $G_{ij} = F_{ij} + F_{ij}^T, i \neq j$ (note that $G_{ij} = G_{ji}$) define the three conics (C_{ij}) which must split each into two lines, hence the six lines $\ell_{12}, \rho_{12}, \ell_{23}, \rho_{23}, \ell_{31}, \rho_{31}$. A **necessary condition** for the motion to be planar is that the six lines ℓ_1, ℓ_2, ℓ_3, and $\ell_{12}, \ell_{23}, \ell_{31}$ are "close" enough.

3. Algebraic Characteristic and Geometric Interpretation of Planar Motion

As we known, at least three different camera views are needed for planar motion detection. Generally, the camera's motion plane can be uniquely determined by their three non-collinear locations of optical centers. [1]

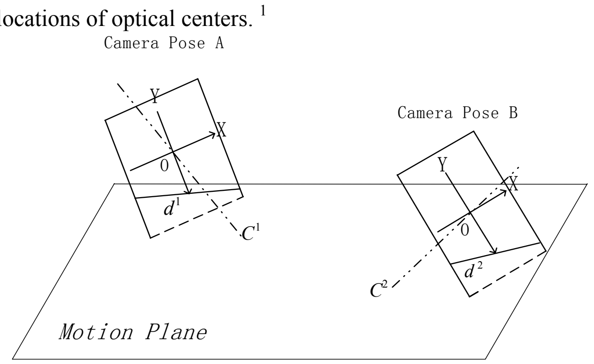

Fig 1: Different positions and orientations of the planar motion cameras.(C^1,C^2 are the optical centers of cameras, OC^1,OC^2 are the optical axes of cameras and XOY is the coordinates in camera retinal planes, d^1,d^2 are the intersected points between Y axis and trifocal lines.)

From a geometric viewpoint, we can give the following theorem:
Theorem: *The motion of a camera is planar if and only if all the trifocal lines in different retinal planes have the same 2D image coordinates in their respective frames.*

Proof: For a general camera pose, we can set up a 3D world coordinates as follows shown in Fig 2:

Camera's optical center C is taken as the original point of 3D world coordinates. Camera motion plane's equation is $Z = 0$, and the normal of motion plane is Z axis in the world coordinates. Optical axis CO locates in the plane ZCY and the inclination between CO and CY is $\angle OCY = \theta$. Assume the focus length is f, so the principle point O in camera's retinal plane is $(0, f\cos(\theta), f\sin(\theta))$. The camera's retinal (image) plane's equation is $f\cos(\theta) \times Y + f\sin(\theta) \times Z - f^2 = 0$, and other two points in retinal plane, X: $(-1, f\cos(\theta), f\sin(\theta))$ and Y: $(0, f\cos(\theta) + \sin(\theta), f\sin(\theta) - \cos(\theta))$, respectively locate on the retinal image's X, Y axis. Since the trifocal line is the intersected line between camera's motion plane and the retinal plane, we can compute any two points on the trifocal line, A: $(1, f/\cos(\theta), 0)$ and B: $(-1, f/\cos(\theta), 0)$. In camera's retinal plane, the trifocal line's equation is definitely parameterized as two factors, the inclination α between the image X axis ($\vec{OX}$) and the trifocal line ($\vec{AB}$), and the distance κ from principle point O to the trifocal line. Now the inclination is $\alpha = 0^o$ and distance is $\kappa = f \times tg(\theta)$.

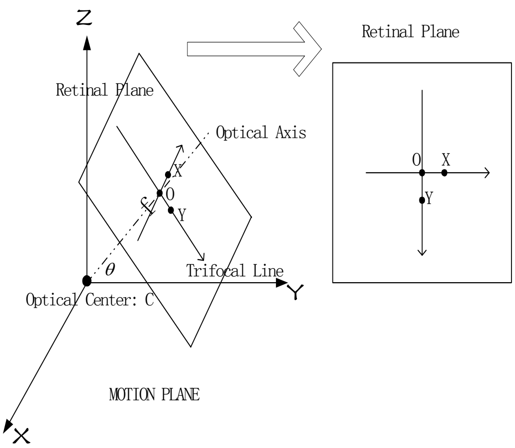

Fig 2: the world coordinates for a certain camera pose while planar motion.

The relative motion between three different camera poses can be decomposed as the translation in the motion plane, the rotation with normal of motion plane, the rotation of camera's optical axis and the rotation with the world X axis. Though these three rotation axes are not totally orthogonal, they can represent any rotation with any axis in the 3D world coordinates by linear combination. This kind of parameterization for

[1] *The optical axis of the camera can never be parallel with the normal of the motion plane during moving. Otherwise, the trifocal line cannot be detected, under this degenerate case.*

rotation also enables us to give an explicit geometric interpretation for camera.

(1) Translation in the motion plane:

Assume the camera's translation is $(a,b,0)$, so principle point O is $(a, b+f\cos(\theta), f\sin(\theta))$, and point X on retinal plane is $(a-1, b+f\cos(\theta), f\sin(\theta))$, then the camera retinal plane's equation is $f\cos(\theta)\times Y + f\sin(\theta)\times Z - f^2 - b\times f\cos(\theta) = 0$. In a similar way, two points on the intersected trifocal line, A: $(a+1, b+f/\cos(\theta), 0)$ and B: $(a-1, b+f/\cos(\theta), 0)$, can be computed from the equations of retinal plane and motion plane. The inclination α between the image X axis ($\vec{OX}$) and the trifocal line ($\vec{AB}$) keeps 0^o, and the distance κ from principle point O to the trifocal line is still $f\times tg(\theta)$.

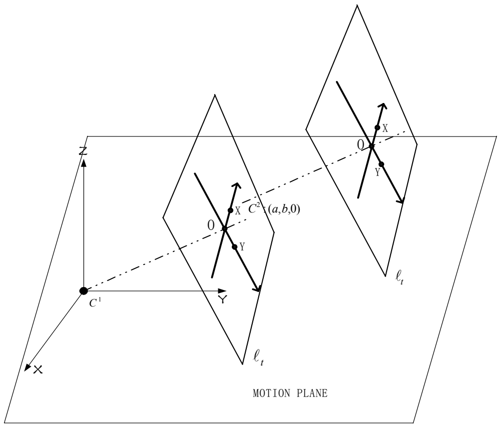

Fig 3: Different locations of camera under a pure tanslation on the motion plane.

(2) Rotation with normal of motion plane:

Assume the rotation angle is φ, so principle point O is $(f\cos(\theta)\sin(\varphi), f\cos(\theta)\cos(\varphi), f\sin(\theta))$, and point X on retinal plane is $(f\cos(\theta)\sin(\varphi)-\cos(\varphi), f\cos(\theta)\cos(\varphi)+\sin(\varphi), f\sin(\theta))$, then the camera retinal plane's equation is $f\cos(\theta)\sin(\varphi)\times X + f\cos(\theta)\cos(\varphi)\times Y + f\sin(\theta)\times Z - f^2 = 0$. In a similar way, two points on the intersected trifocal line, A: $(0, f/(\cos(\theta)\cos(\varphi)), 0)$ and B: $(f/(\cos(\theta)\sin(\varphi)), 0, 0)$, can be computed from the equations of retinal plane and motion plane. The inclination α between the image X axis ($\vec{OX}$) and the trifocal line ($\vec{AB}$) keeps 0^o, and the distance κ from principle point O to the trifocal line is still $f\times tg(\theta)$, unrelated with the value of φ.

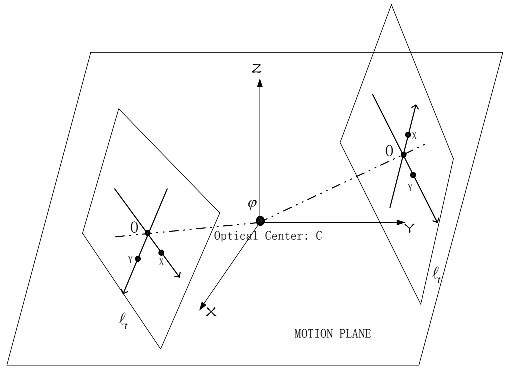

Fig 4: Different poses of camera rotating with normal of the motion plane.

(3) Rotation of camera's optical axis:

Since the camera is rotating round its normal (optical axis), the coordinates of principle point O, the equation of retinal plane and the trifocal line are unchanged. However, the coordinates of image point X become $(-\cos(\varphi), f\cos(\theta)-\sin(\varphi)\sin(\theta), f\sin(\theta)-\sin(\varphi)\cos(\theta))$. The inclination α between the image X axis ($\vec{OX}$) and the trifocal line ($\vec{AB}$) changes to exactly the rotation angle φ, and the distance κ from principle point O to the trifocal line still keeps $f\times tg(\theta)$.

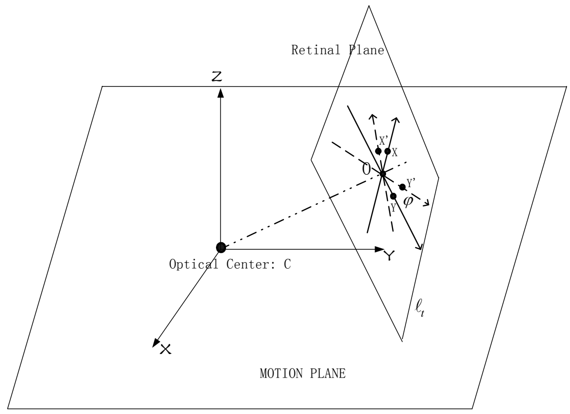

Fig 5: Different poses of camera rotating with its optical axis.

(4) Rotation with the world X axis:

In this case, it means the inclination θ between optical axis CO and world axis CY is variable. From the initial set up the world coordinates and camera systems, we know the inclination α between the image X axis ($\vec{OX}$) and the trifocal line ($\vec{AB}$) is unrelated with value of θ, while the distance κ from principle point O to the trifocal line will change, up to $f\times tg(\theta)$.

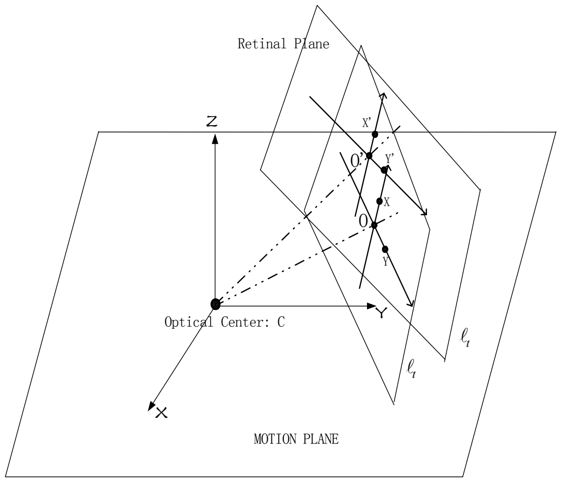

Fig 6: Different poses of camera rotating with world coordinates X axis.

Until now, we have enumerated the geometric coordinates of the trifocal line in the 2D retinal image, under all possible motion cases. According to the definition of planar motion, we know that case 1 and 2 are valid planar motions, while the trifocal lines in different retinal planes have the same 2D image coordinates in their respective frames. If the camera's motion violate the planar motion constrain, either the inclination α between the image X axis ($\vec{OX}$) and the trifocal line ($\vec{AB}$), or the distance κ from principle point O to the trifocal line changes.

Geometric Interpretation: Based on the above analysis, we know there are two different kinds of changes of the trifocal lines' image coordinates in their perspective views, while in case 3 and case 4. In case 3, camera is rotating around its optical axis, which cause the direction α of the trifocal line changes exactly the same angle of camera movement in the image views. If camera's optical axis is not even orthogonal to the retinal plane, the distance κ will also change a little. In case 4, only the distance κ is varying, and the trifocal line is just moving parallelly in the image plane.

For a general camera rotation, it equals to a linear combination of above three kinds of rotation effects. Except the valid planar motion case 2, any other camera rotation must have non-zero components of case 3 or case 4. Further more, these two change effects of the trifocal line's image coordinates with different views cannot counteract.

If we have more than three camera views, their optical centers must lie on the same plane. Then the algebraic and geometric properties of planar motion are the same with three-view case. In real experiments, camera easily oscillates while moving. Robust estimation method can be employed to find the most stable views, which are coherent with the same planar motion.

Remark 1: *The trifocal line is taken as the image coordinate axis of 1D camera in [1]. From the general 2D camera, we know that the image coordinates system is invariant and known as a prior knowledge. This invariance is also necessary for 1D camera, or it cannot be determined that the unique original point in each 1D image coordinates.*

4. Robust Estimation of The Trifocal Line on Three Different Cases

From the above theorem, we can simplify the ***planar motion detection*** problem as ***the collinearity of all image epipoles*** on different camera views under the same planar motion, since they must be on the same image trifocal line for a real planar motion. This problem will be discussed in the following three different cases of planar motion. Here, we only discuss three camera views, and more views analysis can be easily extended with a similar way.

(1). Three positions of the camera center compose a triangle in the motion plane (**PM-T** method).

In this case, there exist two epipoles in each image, $e_{12}, e_{13}, e_{21}, e_{23}, e_{31}, e_{32}$, which are all used to fit an image trifocal line ℓ_t by linear Least-Square method. Then the planarity of camera motions can be directly evaluated by the line-fitting residual errors.

$$Error = \sum_i \sum_j dist(e_{ij}, \ell_t) \quad i, j = 1,2,3, \; i \neq j$$

where $dist(e_{ij}, \ell_t)$ means the Euclidean distance between epipoles and the trifocal line in the images.

From the above, we have got the trifocal line using all the information provided by epipoles, so it is more robust than the method in Faugeras et al [1]. The unique formulation of the trifocal line is also very necessary to be taken as the 1D image coordinate axis. And we can see the inconsistent formulations of the trifocal line bring large deviations for 1D trifocal tensor estimation in Faugeras et al [1].

(2). Three camera positions are on the same line of the motion plane (**PM-L** method).

In this case, there exists only one epipole in each image, e_1, e_2, e_3, which can also be used to fit the trifocal line ℓ_t by least-square method. In the same way, the planarity of the motion can be evaluated this line-fitting residual error.

$$Error = \sum_i dist(e_i, \ell_t) \quad i = 1,2,3$$

In this case, it is impossible to estimate the trifocal line ℓ_t from only one epipole in each image, so **FM** method will degenerate. While our method still work well by using all three epipoles of different images to estimate the trifocal line, unless there are no rotation between different poses of the camera. The three epipoles will have the same 2D coordinates if that is the case, so the trifocal line cannot be detected.

Remark 2: *In the real applications, this kind of camera motion configuration is much easier to be implemented, compared with PM-T. Actually, we design a simple vision system with a camera moving along a bar, which can pan and tilt. Empirically to say, the estimation accuracy of the trifocal line is also good, if the* *relative rotations between different camera poses are well handled.*

(3). While the camera is undergoing the stationary rotation, both methods will fail because the epipoles do not exist in any image. However, Hartley's camera calibration method [19] can be applied to this configuration.

5. Analysis of Uncertainty Projections (2D to 1D)

The estimation of the trifocal line is very critical for camera self-calibration, since it forms the retinal line for the virtual 1D camera. On the other hand, in order to estimate the 1D trifocal tensor used by camera self-calibration, the ordinary matching points in 2D images must be projected onto the trifocal line as new 1D points [1]. For a pair of matching points in one image, we link them as a line and the intersected point with the trifocal line is taken as a point for 1D virtual camera. In the other image, the corresponding pair of 2D points forms a new line, and gets a new intersection with the trifocal line in that image. This new intersection is exactly the corresponding point for that 1D point. It means the virtual 1D points are just determined by the selection of a pair of initial 2D image points and the position of the trifocal line.

For a certain matching point, we can assume the correct candidate locates within its neighborhood in the image. In Fig. 7, the uncertainty of matching points: A1, A2, B1, B2, C1, C2, can be described as a circle region around each of them. The uncertainty propagation of matching points from 2D to 1D is up to two essential factors. One factor is the distance ratio among a pair of points, such as A1, A2, and the intersected points A3. The other is inclination β between line: A1A2 and the trifocal line.

We propose the following criterion for the selection of the pair of 2D image points, once the trifocal line has been estimated.

*Case **A**:*

$Dist(A1, A2) > Dist(A1, A3)$ *and* $Dist(A1, A2) > Dist(A2, A3)$

*Case **C:***

$Dist(C1, C2) < Dist(C1, C3)$ *and* $Dist(C1, C2) < Dist(C2, C3)$

*Case **B:***

$Dist(B2, B3) < Dist(B1, B2) < Dist(B1, B3)$ *or*

$Dist(B1, B3) < Dist(B1, B2) < Dist(B2, B3)$

As shown in Fig 7, the uncertainties of 1D points under three cases are respectively represented as: $\phi^A = (a1, a2)$, $\phi^B = (b1, b2)$ and $\phi^C = (c1, c2)$. Only case A is effective for 1D points' projection, which keeps the same level of uncertainty from initial matching points. In case B and case C, the uncertainty is magnified for 1~2 times and more than 2 times respectively. In order to ensure the estimation accuracy of 1D trifocal tensor T_{ijk}, only matching pairs according to case A are considered valid. Then we pick up the pairs, direct ration the inclination β between pair-line, such as A1A2 and the trifocal line. The uncertainty range of case A can be computed from $2r / \sin(\beta)$, where r is the radius of uncertainty circle for initial 2D matching points. Until now, we can see that the initial matching error may be ill magnified with the 2D-1D projection, but it still can be well handled through our analysis.[2]

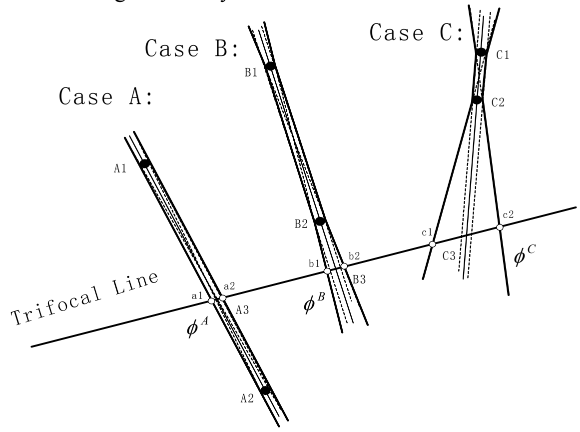

Fig 7: the projection from 2D image points to 1D image points. (• is the distribution area of the random uncertainty for 2D image points. The black lines are the bound of uncertainty for the 2D-1D projection. Here, **A, B, C** are three cases of 2D to 1D projections.)

After the projections from 2D image points to 1D image points, we got many triplets of 1D corresponding points from three camera views. Any triplet of corresponding points $f \leftrightarrow f' \leftrightarrow f''$ satisfies a tri-linear relation, known as the trifocal tensor constraint:

$$T_{ijk} f^i f'^j f''^k = 0 \quad (i, j, k = 1,2)$$

Then we can linearly estimate the trifocal tensor T_{ijk} by at least 7 triplets. Once T_{ijk} line is obtained, the two images of circular points on the line projection of the motion plane on the infinite plane is also got by

$$T_{ijk} u^i u^j u^k = 0 \quad (i, j, k = 1,2)$$

With five images of circular points corresponding to three different planar motions, the image of Absolute Conic [20] can be linearly fitted by $(u,v,1)(K^{-1})^T (K^{-1})(u,v,1)^T = 0$, where $(u,v,1)$ is the above circular points' original 2D image coordinates. Then the intrinsic parameters K of the camera are also obtained using Cholesky Decomposition [1].

6. Experiments

We tested our method with both simulated and real images. Compared with the results of original method, our experimental results show the advantage of robustness of our method. For more detail information on trifocal line location and camera calibration, please refer to our journal version paper, according to the space problem.

---

2 *Here, we do not discuss the probabilistic distribution function (PDF) of uncertainty projections. It cannot help us to find more robust results. Image matching points in 2D images are the only information we have to form new 1D points. The only choice for 2D-1D projections is to link a pair of 2D points and compute its intersected point with the trifocal line. Based on above analysis, we want to figure out these good projections, which are used for following processes.*

Fig 8. Our 1D camera self-calibration system: with a straight bar mounted on a tripod.

From Fig. 8, we can see that only a straight bar is mounted on the platform of the tripod. Camera is fixed on the bar and can move back and forth along the bar direction and rotate around the normal of the plat-form. It is exactly the second case **PM-L**, while our approach can still work well. By tilting the platform, different planar motions are also achieved. The motion configuration is illustrated from geometric view in Fig. 9.

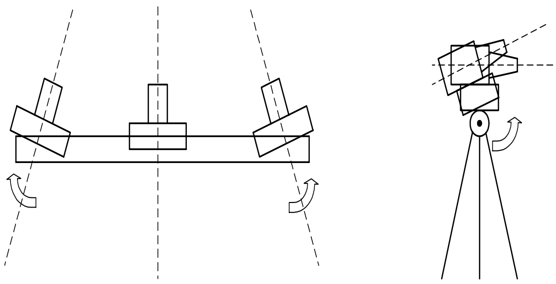

Fig 9. The camera configuration used in the experiments.

7. Conclusion

In this paper, we have proposed an explicit trifocal line position analysis for camera planar motion. It is proved using a special algebraic parameterization method and is interpreted from a geometric view. Our result simplifies the planar motion detection problem. We also distinguished the usage of three different cases of planar motions: ordinary (non-collinear) planar motion, collinear planar motion and stationary planar motion. In order to make this approach of camera self-calibration more feasible, we purposed a method on how to determine and avoid the selection of 2D image point pairs, whose 1D projection points will have more magnified location errors. Experiments using simulated and real images show our new method generally out-performs the original method proposed in [1]. On the other hand, the proposed practical image capture system will facilitate vision applications using 1D linear camera calibration in real environments.

8. Acknowledgement

Many thanks for Dr. Zhan-yi Hu’s many useful discussions.

9. References

[1] O.Faugeras, L.Quan and P.Sturm. *“Self-calibration of a 1D projective camera and its Application to the self-calibration of a 2D projective camera”,* ECCV, 1998.

[2] P.Sturm, *“Critical motion sequences for monocular self-calibration and uncalibrated Euclidean reconstruction”,* CVPR, 1100-1105, 1997.

[3] P.Sturm, *“Critical motion sequences and conjugacy of ambiguous Euclidean reconstructions”,* SCIA, 439-446, 1997.

[4] T.Buchanan, *“The twisted cubic and camera calibration”,* CVGIP, 42(1): 130-132, 1998.

[5] R.Szeliski, *“Video mosaics for virtual environments”,* IEEE Computer Graphics and Applications, 16(2), 22-30, 1996.

[6] H.Shum and R.Szeliski, *“Panoramic image mosaic”,* Technical Report, Microsoft Research.

[7] H.Shum and L.He, *“Rendering with concentric mosaics”,* SIGGRAPH, 1999.

[8] S.J.Maybank and O.Faugeras, *“A theory of self calibration of a moving camera”,* IJCV, 8(2): 123-151, 1992.

[9] Q.-T.Luong and O.Faugeras, *“Self-calibration of a moving camera from point correspondences and fundamental matrices”,* IJCV, 22(3): 261-289, 1997.

[10] C.Rothwell, G.Csurka and O.Faugeras, “A Comparison of Projective Reconstruction Methods for Pairs of Views”, INRIA, Research Report 2538, Apr. 1995.

[11] L.Lu, Z.Hu and H.T. Tsui, *“Sub-sequence Factorization -- An Effective Approach for Projective Reconstruction”,* ACCV 2000, pp. 1052-1057, Jan. 2000, Taipei, Taiwan, China.

[12] Qian Chen and G. Madioni, *“Efficient Iterative Solution to M-View Projective Reconstruction Problem”*, CVPR 1999, Vol. II: 55-61.

[13] P. Sturm and B. Triggs, *“A factorization based algorithm for multi-image projective structure and motion”,* ECCV 1996.

[14] Mei Han and Takeo Kanade, *“Perspective factorization methods for Euclidean reconstruction”,* CMU-RI-TR-99-22, Robotics Institute, Carnegie Mellon University, Aug. 1999.

[15] Mei Han and Takeo Kanade, *“Scene reconstruction from multiple uncalibrated views”,* CMU-RI-TR-00-09, Robotics Institute, Carnegie Mellon University, Jan. 2000.

[16] Qian Chen and G. Madioni, *“Building Human Face Models from Two Images”*, accepted by Journal of VLSI Signal Processing-Systems for Signal, Image, and Video Technology, Kluwer Academic Publicshers.

[17] L. Lu, H.T. Tsui and Z. Hu, *“A Novel Planar Motion Detection Method and the Robust Estimation of 1D Trifocal Tensor”*, ICPR 2000, Vol. 3, pp. 815-818, Sep. 2000, Barcelona, Spain.

[18] L. Quan, L. Lu, H.Y. Shum, M. Lhuillier, *“Concentric Mosaic(s), Planar Motion and 1D Cameras”*, to appear in International Conf. on Computer Vision, Jul. 2001, Vancouver, Canada

[19] R. Hartley, *“Self-Calibration of Stationary Cameras”*, International Journal of Computer Vision, 22(1), pp. 5-23, 1997.

[20] O. Faugeras, "*Camera Self-Calibration: Theory and Experiment*," European Conf. of Comp. Vision, pp. 321-334, 1992.