New Initialization method for the robust self-calibration of the camera

Jong-Eun Ha*, and Dong-Joong Kang**

* Department of Multimedia Engineering, Tongmyong University of Information Technology, Busan, Korea
(Tel : +82-51-610-8416; E-mail: jeha@tit.ac.kr)

**Department of Mechatronics Engineering, Tongmyong University of Information Technology, Busan, Korea
(Tel : +81-51-610-8361; E-mail: djkang@tit.ac.kr)

Abstract: Recently, 3D structure recovery through self-calibration of camera has been actively researched. Traditional calibration algorithm requires known 3D coordinates of the control points while self-calibration only requires the corresponding points of images, thus it has more flexibility in real application. In general, self-calibration algorithm results in the nonlinear optimization problem using constraints from the intrinsic parameters of the camera. Thus, it requires initial value for the nonlinear minimization. Traditional approaches get the initial values assuming they have the same intrinsic parameters while they are dealing with the situation where the intrinsic parameters of the camera may change. In this paper, we propose new initialization method using the minimum 2 images. Proposed method is based on the assumption that the least violation of the camera's intrinsic parameter gives more stable initial value. Synthetic and real experiment shows this result.

Keywords: self-calibration, camera calibration, 3D recovery, initialization

1. INTRODUCTION

Recently, 3D structure recovery through self-calibration of camera has been actively researched. Traditional calibration algorithm requires known 3D coordinates of the control points while self-calibration only requires the corresponding points of images, thus it has more flexibility in real application. In general, self-calibration algorithm results in the nonlinear optimization problem using constraints from the intrinsic parameters of the camera. Thus, it requires initial value for the nonlinear minimization. Traditional approaches get the initial values assuming they have the same intrinsic parameters while they are dealing with the situation where the intrinsic parameters of the camera may change.

Faugeras et al. [1] proposed a self-calibration algorithm which uses the Kruppa equation. It enforces that the planes through two camera centers which are tangent to the absolute conic should also be tangent to both of its images. Hartley [2] proposed another method based on the minimization of the difference between the internal camera parameters for the different views. Polleyfeys et al. [3] proposed a stratified approach that first recovers the affine geometry using the modulus constraint and then recovers the Euclidean geometry through the absolute conic. Heyden & Åström [4], Triggs [5] and Pollefeys & Van Gool [6] use explicit constraints that relate the absolute conic to its images. These formulations are especially interesting since they can easily be extended to deal with the varying internal camera parameters.

Recently self-calibration algorithms that can deal with the varying camera's intrinsic parameters were proposed. Heyden & Åström [7] proposed a self-calibration algorithm that uses explicit constraints from the assumption of the intrinsic parameters of the camera. They proved that self-calibration is possible under varying cameras when the assumptions that the aspect ratio was known and no skew establishes about the camera. They solved the problem using the bundle adjustment that requires simultaneous minimization on the all reconstructed points and cameras. Moreover, the initialization problem was not properly presented. Bougnoux [8] proposed a practical self-calibration algorithm that used the constraints derived from Heyden & Åström [7]. He proposed the linear initialization step in the nonlinear minimization. He used the bundle adjustment in the projective reconstruction step. Similarly, Pollefeys et al. [9] proposed a versatile self-calibration method that can deal with a number of types of constraints about the camera. They showed a specialized version for the case where the focal length varies, possibly also the principal point.

In this paper, we propose new initialization method for the self-calibration algorithm by using the minimal two images, which result in the more stable initial values for the nonlinear minimization. This results in the solving of the simultaneous equations of the second-order, and gives two solutions that have opposite direction in projective space.

New initialization method for the self-calibration of the camera is proposed. Proposed method is based on the assumption that the least violation of the camera's intrinsic parameter gives more stable initial value. Synthetic and real experiment shows this result. Finally we can have more robust self-calibration algorithm based on the proposed initialization method

2. SELF-CALIBRATION ALGORITHM

In this section, we review the self-calibration algorithm that appears in [8]. The process of projection of a point in 3D to the image plane can be represented as the following sequential steps:

$$\mathbf{P}_{euc} = \mathbf{A}\mathbf{P}_0\mathbf{T} = \begin{bmatrix} \alpha_u & \gamma & u_0 \\ 0 & \alpha_v & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}_3^T & 1 \end{bmatrix} \tag{1}$$

where $\mathbf{T}$ represents the transformation of coordinate systems from world to the camera-centered system, $\mathbf{P}_0$ is the perspective projection and $\mathbf{A}$ consists of the intrinsic parameters of camera.

We use the following assumptions about the intrinsic parameters of camera

$$\begin{aligned} \gamma &= 0 \\ \alpha_u &= \alpha_v \end{aligned} \tag{2}$$

It is well known that we can reconstruct a scene up to a projective transformation using only the corresponding points on the images [10,11]. This can be represented as:

$$\tilde{\mathbf{m}}_j^i \cong \mathbf{P}_{proj}^i \tilde{\mathbf{M}}_j^{proj} = \mathbf{P}_{proj}^i \mathbf{Q}\mathbf{Q}^{-1} \tilde{\mathbf{M}}_j^{proj} \tag{3}$$

where $\tilde{\mathbf{m}}_j^i$ is the j-th point in the i-th image, $\mathbf{P}_{proj}^i$ is a projective projection matrix of the i-th image and $\tilde{\mathbf{M}}_j^{proj}$ is a projective structure of scene point corresponding to the image point $\tilde{\mathbf{m}}_j^i$.

The projective structure $\tilde{\mathbf{M}}_j^{proj}$ is related to the metric structure by a projective transformation matrix $\mathbf{Q}$. In Eq. (3), any nonsingular matrix $\mathbf{Q}$ satisfies the above relation, so there can be many projective reconstructions. There exists a unique $\mathbf{Q}$ matrix that transforms the projective structure to a metric structure of a given scene. Finding this $\mathbf{Q}$ matrix is calibration process. We can obtain the Euclidean projection matrix and metric structure of a scene using this unique $\mathbf{Q}$ matrix.

$$\begin{aligned} \mathbf{P}_{euc}^i &\cong \mathbf{P}_{proj}^i \mathbf{Q} \\ \tilde{\mathbf{M}}_j^{euc} &\cong \mathbf{Q}^{-1} \tilde{\mathbf{M}}_j^{proj} \end{aligned} \tag{4}$$

In general, under the pinhole camera model, we can set the projective projection matrix of the first camera as $\mathbf{P}_{proj}^1 = [\mathbf{I}_3 \quad \mathbf{0}_3]$. We have the Euclidean projection matrix of the first camera $\mathbf{P}_{euc}^1 = [\mathbf{A}_1 \quad \mathbf{0}_3]$ if we set the world coordinate at the optical center of the first camera. If we substitute these projection matrices in Eq. (4), then we have

$$\begin{aligned} \mathbf{P}_{euc}^1 \cong \mathbf{P}_{proj}^1 \mathbf{Q} &\Leftrightarrow [\mathbf{A}_1 \quad \mathbf{0}_3] \cong [\mathbf{I} \quad \mathbf{0}_3]\mathbf{Q} \\ &\Leftrightarrow \exists(\mathbf{q}, q_{44}) \mid \mathbf{Q} \cong \begin{bmatrix} \mathbf{A}_1 & \mathbf{0}_3 \\ \mathbf{q}^T & q_{44} \end{bmatrix} \end{aligned} \tag{5}$$

Here, $\mathbf{Q}$ is defined up to a scale and it can be represented as

$$\mathbf{Q} = \begin{bmatrix} f & 0 & u_0 & 0 \\ 0 & f & v_0 & 0 \\ 0 & 0 & 1 & 0 \\ q_1 & q_2 & q_3 & 1 \end{bmatrix} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{0}_3 \\ \mathbf{q}^T & 1 \end{bmatrix} \quad (f \equiv \alpha_u, \alpha_v) \tag{6}$$

Now $\mathbf{Q}$ matrix contains six unknowns. Next we review the constraint for obtaining $\mathbf{Q}$ matrix.

If we set $\mathbf{P}_{euc}^i$

$$\mathbf{P}_{euc}^i \cong \mathbf{P}_{proj}^i \mathbf{Q} = \begin{bmatrix} \mathbf{p}_1^{iT} & \\ \mathbf{p}_2^{iT} & \mathbf{t}_i \\ \mathbf{p}_3^{iT} & \end{bmatrix} \tag{7}$$

then we have the following constraint for the Euclidean projection matrix, $\mathbf{P}_{euc}$.

$$\begin{aligned} \gamma = 0 &\Leftrightarrow (\mathbf{p}_1 \times \mathbf{p}_3) \bullet (\mathbf{p}_2 \times \mathbf{p}_3) = 0 \\ \alpha_u = \alpha_v &\Leftrightarrow \|\mathbf{p}_1 \times \mathbf{p}_3\| = \|\mathbf{p}_2 \times \mathbf{p}_3\| \end{aligned} \tag{8}$$

These equations give two constraints for the unknown $\mathbf{Q}$ matrix for each camera and we can obtain the solution using at least 4 images. The resulting problem can be formulated as the nonlinear estimation that minimizes Eq. (8) for each camera.

In [12], we added another constraint which constrain the position of the principal point during the nonlinear minimization.

3. NEW INITIALIZATION METHOD AND DETAILED PROCEDURES

3.1 New Initialization Method

We need initial values to run the nonlinear minimization. The cost function of Eq. (8) has many local minima. Thus, it is important to have good initial values close to the true ones to guarantee the convergence. The initial value by [8] often does not guarantee convergence. This is due to the fact that least-squares solution under the assumption that intrinsic parameters are constant under the varying cameras makes the initial values even worse. We propose new initialization method for the $(q_1, q_2, q_3)^T$ using only two views, thus guarantee the least violation of the varying camera situation.

Euclidean projection matrix can be represented as:

$$\mathbf{P}_{euc}^i = \mathbf{A}_i [\mathbf{R}_i \, \mathbf{t}_i]$$

where $\mathbf{A}_i$ is the matrix consisted of the intrinsic parameters, $\mathbf{R}_i$ is rotation matrix and $\mathbf{t}_i$ is translation vector. Also if we denote $\mathbf{Q}^*$ as the first three column of the matrix Q, we can derive following relations from Eq. (4).

$$\mathbf{A}_i \mathbf{R}_i \cong \mathbf{P}_{proj}^i \mathbf{Q}^* \tag{9}$$

From Eq. (9), it follows

$$\begin{aligned} (\mathbf{A}_i \mathbf{R}_i)(\mathbf{A}_i \mathbf{R}_i)^T &\cong (\mathbf{P}_{proj}^i \mathbf{Q}^*)(\mathbf{P}_{proj}^i \mathbf{Q}^*)^T \\ \omega_k &\cong \mathbf{P}_{proj}^i \Omega \, \mathbf{P}_{proj}^{i\,T} \quad \left(\omega_k = \mathbf{A}_i \mathbf{A}_i^T, \ \Omega = \mathbf{Q}^* \mathbf{Q}^{*T}\right) \end{aligned} \tag{10}$$

ω_k is the dual image absolute conic and Ω is the absolute dual quadric.

From Eq. (10), we obtain

$$\lambda_i \begin{bmatrix} f_i^2 + u_0^2 & u_0 v_0 & u_0 \\ u_0 v_0 & f_i^2 + v_0^2 & v_0 \\ u_0 & v_0 & 1 \end{bmatrix} = \mathbf{P}_{proj}^i \begin{bmatrix} f_1^2 + u_0^2 & u_0 v_0 & u_0 & f_1 q_1 + u_0 q_3 \\ u_0 v_0 & f_1^2 + v_0^2 & v_0 & f_1 q_2 + v_0 q_3 \\ u_0 & v_0 & 1 & q_3 \\ f_1 q_1 + u_0 q_3 & f_1 q_2 + v_0 q_3 & q_3 & \|\mathbf{q}\|^2 \end{bmatrix} \mathbf{P}_{proj}^{iT} \tag{11}$$

We use f computed from the algorithm in [8], and take the initial value of the principle point as the center of the first image. Then, we are left with four unknowns λ_i, $(q_1, q_2, q_3)^T$, and Eq. (10) provides 6 equations. We compute the unknowns using four equations. Thus, we avoid the false initial value by least-squares by overconstrained equations. Experimental results support this fact.

3.2 Equalization of the projective basis

At first, projective reconstruction is done using the corresponding points. Fundamental matrix between each view is obtained using the linear normalization method of Hartley [13], then projective projection matrix is obtained using Fundamental matrix. Through the triangulation projective structure is obtained. Projective reconstruction is done using each pair of images such as 1-2, 1-3, …, 1-N. Each projective reconstruction has different bases because the five basis points in P^3 are not equal in each case. If we use the method of Fageraus [12], which explicitly selects the five basis points in P^3, we can obtain consistent projective reconstruction. But, this method is known as sensitive to the selection of five basis points and entire process solely depend on the basis selection. It is necessary to equalize the projective reconstruction in equal basis, because Eq. (3) establishes under equal basis. This problem becomes to finding the collineation between two 3D projective reconstructions.

Given fundamental matrix $\mathbf{F}_a$ that describe the epipolar geometry between two images, there exist a projective basis of the projective space P^3 such that the projections from P^3 space onto the images are represented by two 3X4 projection matrices [14,15]:

$$\mathbf{P}_a = [\mathbf{I}_{3\times3} \ \mathbf{0}_3] \quad \mathbf{P}'_a = [\mathbf{D}'_{3\times3} \ \mathbf{e}'_a] \tag{12}$$

where $\mathbf{D}'_{3\times3}$ is a homography matrix and $\mathbf{e}'_a$ is the epipole of the second image.

If $\mathbf{x}, \mathbf{x}'$ are the image point of a 3D point M, we can obtain the projective coordinate $\mathbf{X}_a$ of point M in the projective basis B_a defined by $(\mathbf{P}_a, \mathbf{P}'_a)$ using the projection $\lambda_x \mathbf{x} = \mathbf{P}_a \mathbf{X}_a$ and $\lambda'_x \mathbf{x}' = \mathbf{P}'_a \mathbf{X}_a$.

Consider another pair of images and corresponding fundamental matrix is $\mathbf{F}_b$. From this pair, equally we can obtain the new projective matrices

$$\mathbf{P}_b = \begin{bmatrix}\mathbf{I}_{3\times3} & \mathbf{0}_3\end{bmatrix} \quad \mathbf{P}'_b = \begin{bmatrix}\mathbf{D}'_{3\times3} & \mathbf{e}'_b\end{bmatrix} \tag{13}$$

From this, we can obtain the projective coordinate $\mathbf{X}_b$ of point M in the projective basis B_b using the projection $\lambda_y \mathbf{y} = \mathbf{P}_b \mathbf{X}_b$ and $\lambda'_y \mathbf{y}' = \mathbf{P}'_b \mathbf{X}_b$.

If we have a set of m points, and let their projective coordinate $\mathbf{X}_a^1, \mathbf{X}_a^2, ..., \mathbf{X}_a^m$ and $\mathbf{Y}_b^1, \mathbf{Y}_b^2, ..., \mathbf{Y}_b^m$ be their homogenous coordinate in the projective basis B_a respectively B_b. Then, there exists a 4X4 collineation matrix H that maps the points $\mathbf{X}_a^i$ to the points $\mathbf{X}_b^i$:

$$\mu_i \mathbf{X}_b^i = \mathbf{H}\mathbf{X}_a^i \tag{14}$$

where μ_i is a scale factor with non-zero values.

Eq. (14) gives three constraints for each pair $(\mathbf{X}_a^i, \mathbf{X}_b^i)$, thus we can obtain H which have 15 degrees of freedom using at least five point correspondences. This simple linear method is sensitive to the noise, which only uses the minimum number of points to compute H, thus it is a better method to use all the corresponding points to obtain H.

The following is the linear method in [16]. They showed linear, nonlinear, and robust method in finding the collineation between two projective reconstructions. They also insist that for levels of noise below one pixel in magnitude, the linear methods performs as well as the non-linear method and hence the linear method should be preferred because it is less time consuming than the non-linear method.

If scale, μ_i, is eliminated, three homogenous linear equations are obtained as follows:

$$\begin{aligned} X_b^{i(4)} V^{i(1)} - X_b^{i(1)} V^{i(4)} &= 0 \\ X_b^{i(4)} V^{i(2)} - X_b^{i(2)} V^{i(4)} &= 0 \\ X_b^{i(4)} V^{i(3)} - X_b^{i(3)} V^{i(4)} &= 0 \end{aligned} \tag{15}$$

where $X_b^{i(j)}$ is the j-th component of vector $\mathbf{X}_b^i$ and $\mathbf{V}^i = \left(V^{i(1)}, V^{i(2)}, V^{i(3)}, V^{i(4)}\right)^T$, from the vector $\mathbf{H}\mathbf{X}_a^i$.

Three additional constraints are introduced, which are not independent from the previous ones, to play the same role for all four projective coordinates.

$$\begin{aligned} X_b^{i(2)} V^{i(1)} - X_b^{i(1)} V^{i(2)} &= 0 \\ X_b^{i(3)} V^{i(1)} - X_b^{i(1)} V^{i(3)} &= 0 \\ X_b^{i(3)} V^{i(2)} - X_b^{i(2)} V^{i(3)} &= 0 \end{aligned} \tag{16}$$

If we denote $\mathbf{h} = (H_{11}, H_{12}, H_{13}, ..., H_{44})^T$, the Eq. (15) and Eq. (16) can be written in the form:

$$\mathbf{B}_i \mathbf{h} = \mathbf{0}$$

where $\mathbf{B}_i$ is 6X16 matrix:

$$\mathbf{B}_i = \begin{pmatrix} X_b^{i(4)} \mathbf{X}_a^{i\,T} & \mathbf{0}_4^T & \mathbf{0}_4^T & X_b^{i(1)} \mathbf{X}_a^{i\,T} \\ \mathbf{0}_4^T & X_b^{i(4)} \mathbf{X}_a^{i\,T} & \mathbf{0}_4^T & X_b^{i(2)} \mathbf{X}_a^{i\,T} \\ \mathbf{0}_4^T & \mathbf{0}_4^T & X_b^{i(4)} \mathbf{X}_a^{i\,T} & X_b^{i(3)} \mathbf{X}_a^{i\,T} \\ X_b^{i(2)} \mathbf{X}_a^{i\,T} & X_b^{i(1)} \mathbf{X}_a^{i\,T} & \mathbf{0}_4^T & \mathbf{0}_4^T \\ X_b^{i(3)} \mathbf{X}_a^{i\,T} & \mathbf{0}_4^T & X_b^{i(1)} \mathbf{X}_a^{i\,T} & \mathbf{0}_4^T \\ \mathbf{0}_4^T & X_b^{i(3)} \mathbf{X}_a^{i\,T} & X_b^{i(2)} \mathbf{X}_a^{i\,T} & \mathbf{0}_4^T \end{pmatrix}$$

Given m correspondences $(\mathbf{X}_a^i, \mathbf{X}_b^i)$, h is obtained through the minimization of the following error function:

$$\sum_{i=1}^{m} \|\mathbf{B}_i \mathbf{h}\|^2 = \mathbf{h}^T \left(\sum_{i=1}^{m} \mathbf{B}_i^T \mathbf{B}_i \right) \mathbf{h}. \tag{17}$$

The solution h is the eigenvector of B, $\mathbf{B} = \sum_{i=1}^{m} \mathbf{B}_i^T \mathbf{B}_i$, corresponding to the smallest eigenvector of B, this eigenvector can be effectively computed using the Singular Value Decomposition.

Following method for homography between projective structure is from the structure of the original projection matrices. From Eq. (13), projection matrix of the first camera has the form, $\begin{bmatrix}\mathbf{I}_{3\times3} & \mathbf{0}_3\end{bmatrix}$, and the corresponding projection equation on the image is

$$\lambda \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix}\mathbf{I}_{3\times3} & \mathbf{0}_3\end{pmatrix} \begin{pmatrix} p \\ q \\ r \\ s \end{pmatrix} \tag{18}$$

From this projection, projective structure, $(p\ q\ r\ s)^T$, has the form of $(x\ y\ 1\ v)^T$. The projective reconstruction for the same point from the pairs of image 1-2,1-3,…,1-N using the projection matrix of Eq. (13) has also the form of $(x\ y\ 1\ v)^T$, where the fourth component has different value according to the chosen projective basis in P^3. From this particular form of the projective structure, the homography between two projective reconstructions has the form:

$$\mathbf{H} = \begin{pmatrix} h_1 & 0 & 0 & 0 \\ 0 & h_1 & 0 & 0 \\ 0 & 0 & h_1 & 0 \\ h_2 & h_3 & h_3 & 1 \end{pmatrix} \tag{19}$$

In this paper, the homography between two projective reconstructions are also computed using Eq. (19).

3.3 Method to get the true value of the plane at infinity

It is necessary to know all the true value of unknown parameters to check the proposed algorithm using the synthetic image. Except the value of $\mathbf{q} = (q_1, q_2, q_3)^T$, all other values are easily obtained in the experiment using synthetic image. One possible method is to set the value of $\mathbf{q} = (q_1, q_2, q_3)^T$ arbitrary, and then obtains the projective projection matrix using the relation $\mathbf{P}_{proj}^i \cong \mathbf{P}_{euc}^i \mathbf{Q}^{-1}$. But this procedure can't analyze the algorithm from the given correspondence. Projective projection matrix is obtained using the fundamental matrix, which is computed using the correspondence. Thus, other method for computing $\mathbf{q} = (q_1, q_2, q_3)^T$ is necessary to analyze proposed algorithm at every step from the very beginning. The method in [16], which computes the homography between Euclidean structure and projective structure, is used.

From the known value of intrinsic and extrinsic parameters true fundamental matrix is computed, then true projective projection matrices are computed. From these projective projection matrices, projective structure is computed using the correspondence without noise. Finally, $\mathbf{q} = (q_1, q_2, q_3)^T$ is computed from the homography between Euclidean structure and projective structure.

Let $\overline{\mathbf{Y}}_i = \left(Y_i^{(1)}, Y_i^{(2)}, Y_i^{(3)}\right)$ be the Euclidean coordinate of a point M in 3D under some Euclidean basis B_E and $\mathbf{X}_i$, a homogenous 4-vector, be the 3D projective coordinates of a point M. Using at least 5 corresponding points between $\mathbf{X}_i$ and $\overline{\mathbf{Y}}_i$, one can compute the collineation H that maps $\mathbf{X}_i$ onto $\mathbf{Y}_i = \left(\overline{\mathbf{Y}}_i^T\ 1\right)^T$. Linear method can be employed to compute the collineation H. However, linear method minimizes algebraic distance. In [16], a linear method that minimizes an Euclidean rather than an algebraic error function is presented. Let the $\overline{\mathbf{V}}_i$ be

$$\overline{\mathbf{V}}_i = \left(\frac{(\mathbf{HX}_i)^{(1)}}{(\mathbf{HX}_i)^{(4)}}, \frac{(\mathbf{HX}_i)^{(2)}}{(\mathbf{HX}_i)^{(4)}}, \frac{(\mathbf{HX}_i)^{(3)}}{(\mathbf{HX}_i)^{(4)}} \right)^T \qquad (20)$$

where $(\mathbf{HX}_i)^{(i)}$ is the i-th component of vector $\mathbf{HX}_i$.
The error function, composed of Euclidean distance between two points in 3D, to be minimized is

$$\min_{\mathbf{H}} \sum_{i=1}^{n} \varepsilon_i^2 \qquad (21)$$

with

$$\varepsilon_i^2 = \left(\frac{(\mathbf{HX}_i)^{(1)}}{(\mathbf{HX}_i)^{(4)}} - \mathbf{Y}_i^{(1)} \right)^2 + \left(\frac{(\mathbf{HX}_i)^{(2)}}{(\mathbf{HX}_i)^{(4)}} - \mathbf{Y}_i^{(2)} \right)^2 + \left(\frac{(\mathbf{HX}_i)^{(3)}}{(\mathbf{HX}_i)^{(4)}} - \mathbf{Y}_i^{(3)} \right)^2 \qquad (22).$$

It is nonlinear to the parameters of H, thus nonlinear optimization method should be employed. Csurka and Horaud [16] propose a linear method by minimizing an Euclidean distance, which is defined in Fig. 1, in the 4-D vector space.

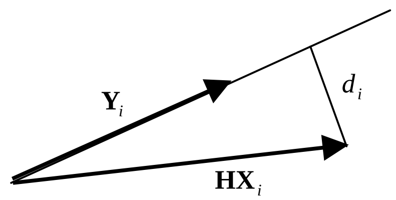


Fig. 1 The approximated Euclidean distance d_i between vectors $\mathbf{Y}_i$ and $\mathbf{HX}_i$ in 4-D vector space.

From Fig. 1 d_i^2 is

$$\begin{aligned} d_i^2 &= (\mathbf{HX}_i)^T(\mathbf{HX}_i) - \frac{(\mathbf{Y}_i^T\mathbf{HX}_i)^2}{\mathbf{Y}_i^T\mathbf{Y}_i} \\ &= \mathbf{X}_i^T\mathbf{H}^T\mathbf{A}_i\mathbf{HX}_i \quad \left(\mathbf{A}_i = \mathbf{I}_{4\times4} - \frac{\mathbf{Y}_i\mathbf{Y}_i^T}{\mathbf{Y}_i^T\mathbf{Y}_i} \right) \end{aligned} \qquad (23).$$

If the following notations are used,

$$\mathbf{HX}_i = \begin{pmatrix} \mathbf{X}_i^T & \mathbf{0}_4^T & \mathbf{0}_4^T & \mathbf{0}_4^T \\ \mathbf{0}_4^T & \mathbf{X}_i^T & \mathbf{0}_4^T & \mathbf{0}_4^T \\ \mathbf{0}_4^T & \mathbf{0}_4^T & \mathbf{X}_i^T & \mathbf{0}_4^T \\ \mathbf{0}_4^T & \mathbf{0}_4^T & \mathbf{0}_4^T & \mathbf{X}_i^T \end{pmatrix} \begin{pmatrix} H_{11} \\ H_{12} \\ \vdots \\ H_{44} \end{pmatrix} = \mathbf{E}_i\mathbf{h} \qquad (24)$$

then the following error function is obtained.

$$d^2 = \sum_i d_i^2 = \mathbf{h}^T \sum_i \left(\mathbf{E}_i^T \mathbf{A}_i \mathbf{E}_i \right) \mathbf{h} = \mathbf{h}^T \mathbf{A} \mathbf{h} \qquad (25)$$

The solution is the eigenvector corresponding to the smallest eigenvalue of the positive semi-definite symmetric matrix A.

4. EXPRERIMENTAL RESULTS

Fig. 2 represents calibration box and control points used in the experiments, and they are acquired by a color CCD camera (Sony EVI-300). Calibration box size is 150mm X 150mm X 150mm. Tsai[17], Bougnoux[8] and proposed algorithm is compared. Table 1 shows the estimated initial f and $\mathbf{q} = (q_1, q_2, q_3)^T$. We can see that proposed method gives more accurate initial values compared to [8]. Fig. 3 represents first and sixth image used in the experiments and the images are acquired varying position and focal length of the camera. Table 2 shows the estimated intrinsic parameters of the camera. Proposed method use additional constraint about the principal point[12] and new initialization method. Table 3 and 4 shows estimated extrinsic parameters. Bougnoux[8] gives large departure from that of Tsai[17] while proposed algorithm gives comparable results. Finally Fig. 4 shows the estimated 3D structure by each algorithm. The unknown scale is set using the first control points between Tsai[17] and other two methods. After fixing the unknown scale, 3D error by all control points compared to the Tsai's method is as follows:

Bougnoux[8]: (mean, std)=(83.1,80.9) [mm]
Proposed algorithm: (mean, std)=(5.91,6.56) [mm]

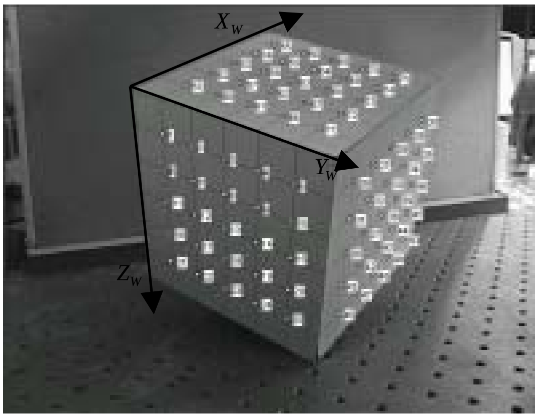


Fig. 2 Calibration box and control points used in the experiments.

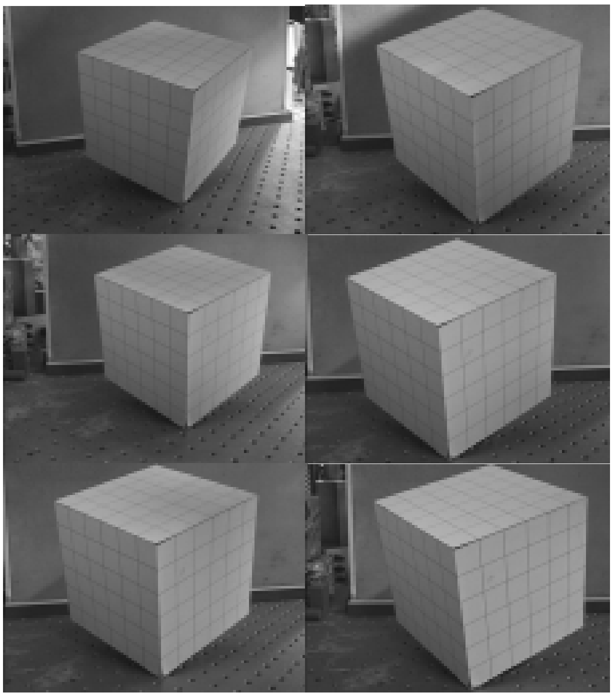


Fig. 3 First and sixth image acquired under the variation of the position and focal length.

Table 1 Comparison of the estimated initial f and $\mathbf{q} = (q_1, q_2, q_3)^T$

true value	linear method[8]	proposed method
758.9, (-50.8,12.3,-36.6)	637.7, (-77.5,0.446,-6.00)	637.7, (-39.7,10.2,-35.1)

Table 2 Comparison of the estimated intrinsic parameters $(\alpha_u, \alpha_v, u_0, v_0)$

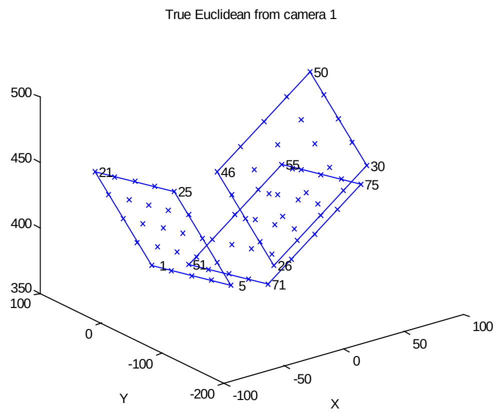
	Tsai[17]	linear method[8]	proposed method
camera 1	(758.9,760.0, 340.4,230.3)	(197.4,197.4, 253.7,229.5)	(605.6,605.6, 283.0,237.3)
camera 2	(880.2,881.0, 352.2,223.2)	(223.1,222.9, 364.7,224.3)	(692.6,691.1, 340.4,230.3)
camera 3	(859.9,861.2, 366.6,220.8)	(206.4,206.5, 339.3,227.6)	(666.5,666.7, 332.9,232.0)
camera 4	(1091.6,1094.1, 332.6,232.1)	(253.1,253.6, 330.3,249.0)	(836.7,835.4, 311.4,248.6)
camera 5	(1007.1,1007.6, 335.4,234.7)	(239.3,239.1, 303.7,242.3)	(777.1,775.6, 298.6,247.4)
camera 6	(1032.0,1034.5, 326.5,231.5)	(252.0,252.0, 418.0,248.8)	(803.5,800.6, 350.4,247.2)

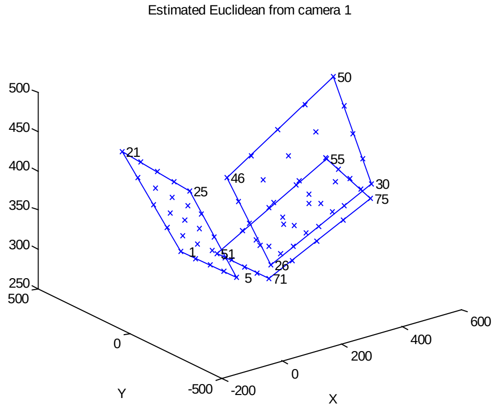
Table 3 Comparison of the estimated rotation $(\theta_x, \theta_y, \theta_z)$ between camera i and j.

	Tsai[17]	linear method[8]	proposed method
1-2	(-1.03,-15.4,-4.07)	(-0.263,-3.97,-3.87)	(-0.869, -12.2,-4.10)
1-3	(1.51,-9.61,-2.66)	(0.372,-2.54,-2.85)	(1.12,-7.89,-2.84)
1-4	(1.04,-15.7,-3.25)	(0.265,-3.98,-3.43)	(0.747,-12.7,-3.46)
1-5	(1.47,-11.1,-1.94)	(0.375,-2.90, 2.15)	(1.13,-9.06,-2.14)
1-6	(0.895,-23.6,-4.39)	(0.233,-5.90,-4.53)	(0.661,-18.6,-4.62)

Table 4 Comparison of the estimated translation between camera i and j.

	Tsai[17]	linear method[8]	proposed method
1-2	(-0.970,0.070,0.234)	(-0.996,0.071,0.061)	(-0.980,0.068,0.189)
1-3	(-0.688,-0.149,0.710)	(-0.945,-0.217, 0.244)	(-0.753,-0.178, 0.633)
1-4	(-0.755,-0.034,0.655)	(-0.979,-0.055,0.197)	(-0.827,-0.047, 0.560)
1-5	(-0.740,-0.119,0.661)	(-0.964,-0.163,0.209)	(-0.808,-0.141,0.572)
1-6	(-0.864,-0.078,0.497)	(-0.987,-0.091,0.131)	(-0.912,-0.087,0.401)





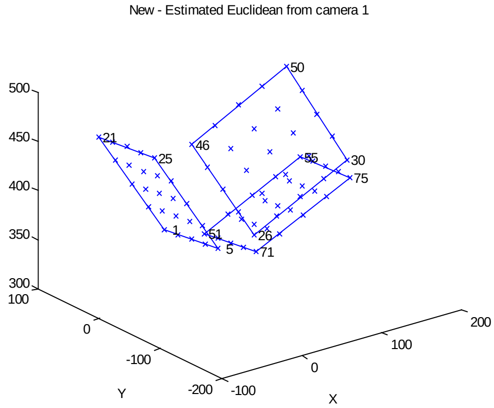


Fig. 4 Estimated 3D structure by Tsai[17], Bougnoux[8], and proposed algorithm.

5. CONCLUSION

New initialization method for the self-calibration using the minimum 2 view is presented. Proposed method is based on the assumption least violation about the camera gives more accurate initial values for the self-calibration. Experimental results using calibration box shows this fact.

Future research will focus on the behavior of plane at infinity in the self-calibration.

REFERENCES

[1] O. Faugeras, Q.-T. Luong, and S. Maybank, "Camera Calibration: Theory and experiments," *Proc, ECCV'92*, pp.321-334, 1992.

[2] R. Hartley, "Euclidean reconstruction from uncalibrated views," *Applications of invariance in Computer Vision*, LNCS 825, Springer-Verlag, 1994.

[3] M. Pollefeys and L. Van Gool, and A. Oosterlinck, "The Modulus Constraint: A New Constraint for Self-Calibration," *Proc. ICPR'96*, pp.349-353, 1996.

[4] A. Heyden, and K. Åström, "Euclidean Reconstruction from Constant Intrinsic Parameters," *Proc. International Conference on Pattern Recognition*, 1996.

[5] B. Triggs. "The Absolute Quadric," *Proc. Computer Vision and Pattern Recognition*, 1997.

[6] M. Pollefeys and L. Van Gool, "Self-calibration from the absolute conic on the plane at infinity," *Proc. CAIP'97*,

1997.

[7] A. Heyden,and K. Åström ,"Euclidean Reconstruction from Image Sequences with Varying and Unknown Focal Length and Principal Point," *Proc. CVPR'97*, 1997.

[8] S. Bougnoux, "From Projective to Euclidean Space under any practical situation, a criticism of self-calibration," *Proc. ICCV'98*, pp.790-796, 1998.

[9] M. Pollefeys, R. Koch and L. Van Gool, "Self-calibration and Metric Reconstruction in Spite of Varying and Unknown Internal Camera Parameters," *Proc. ICCV'98*, pp.90-95, 1998.

[10] O. Faugeras, "What can be seen in three dimensions with an uncalibrated stereo rig?," *Proc. ECCV'92*, pp.563-578, 1992.

[11] R. Hartley, R. Gupta, and T. Chang, "Stereo from uncalibrated cameras," *Proc. CVPR'92*, pp.761-764, 1992.

[12] J.E. Ha, J. Y. Yang, K. J. Yoon, and I. S. Kweon, "Self-calibration using the linear projective reconstruction," *Proceedings of the International Conference on Robotics and Automation*, pp. 885-890, April, 2000.

[13] R. I. Hartley, "In defence of the 8-point algorithm," *Fifth International Conference on Computer Vision*, pp. 1064-1070, 1995.

[14] R. Hartley and P. Sturm, "Triangulation," *Computer Vision and Image Understanding*, Vol. 68, No. 2, pp. 146-157, 1997.

[15] C. Rothwell, O. Faugeras, and G. Csurka, "A comparison of projective reconstruction methods for pairs of views," *Computer Vision and Image Understanding*, Vol. 68, No. 1, pp.36-58, 1997.

[16] G. Csurka and R. Horaud, "Finding the collineation between two projective reconstructions," *INRIA RR-3468*, 1998.

[17] R. Y. Tsai, "A versatile camera calibration technique for high accuracy 3D machine vision metrology using off-the-self TV cameras and lenses." *IEEE Journal of Robotics and Automation*, vol. 3, 1987.