BIULETYN INSTYTUTU AUTOMATYKI I ROBOTYKI WAT
NR 15, 2001

Space Orientation Based on Image from a Mobile Camera[1]

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Abstract. This paper presents the pose parameters estimation algorithm for a mobile camera in each of its position. The algorithm is based on recursive filtration of intermediary results. This feature makes a knowledge accumulation during calibration process possible. The algorithm was verified experimentally. The way of an experiment execution method and received results are described.

1. Introduction

Permanent tracking of a robot pose is needed to control a mobile robot [10],[11]. Conventional methods of a robot position determining basing on a robot navigation system should be verified in other way. Determining the pose of a camera stationary installed on the mobile robot may be used to verify robot's position [6],[7],[10]. Such a method should precisely determine position parameters by using as small number of landmarks as possible and by utilising formerly accumulated position knowledge.

The method of a mobile camera pose estimation, which is presented in this paper, is based on the Ito-Ishii camera calibration algorithm [4],[8]. The method needs at least six non-coplanar landmarks observed in the first frame. In the subsequent frames there may be less then six visible landmarks. The use of a larger number of landmarks usually improves the calibration results. However it is difficult to find and identify a large number of landmarks in the image.

The proposed method can be used to precisely determine the position of the mobile robot in the environment, in which only landmarks positions are known. This method allows an active use of landmarks appearing in the camera view. After finishing the first round of camera calibration process, the accumulated camera position knowledge may be use as a basis for the

[1] This paper was presented at "IMA Third Conference on Imaging and Digital Image Processing: Mathematical Methods, Algorithms and Applications" (Leicester, 13th - 15th September 2000) and is published with the consent of The Institute of Simulation Sciences at De Montfort University.

determination of extrinsic camera parameters for the next position of the camera. All images acquired in the following additional camera position will be used for correction of the predicted "new" position. Hence, in this paper a recursive method of camera position and orientation determining after the camera movement sequence is described.

2. Camera calibration problem

A simplified camera model for a projective mapping showed in Figure 1 is considered [4],[8]. Let us introduce the following notation:

- L - distance between the camera optical centre O_c and the image surface;
- (i_p, j_p) - co-ordinates of the principal point (i.e. the image centre);
- η_i, η_j - scale factors;
- (c_1, c_2, c_3) - position of camera co-ordinates origin (placed in the camera optical centre) given in the world co-ordinates;
- α, β, φ - camera rotation angles around the world co-ordinates axes OX, OY and OZ, respectively.

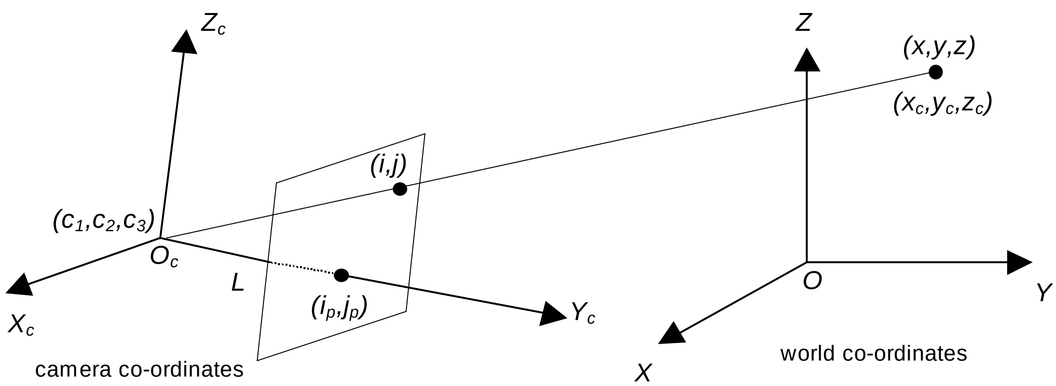

Figure 1. Camera model

The following equations describe relations between the point (x, y, z) in the world co-ordinates and its projections (i, j) in the image:

$$i = \frac{L}{\eta_i} \frac{a_{11}x + a_{12}y + a_{13}z - a_{11}c_1 - a_{12}c_2 - a_{13}c_3}{a_{21}x + a_{22}y + a_{23}z - a_{21}c_1 - a_{22}c_2 - a_{23}c_3} + i_p \;, \tag{1}$$

$$j = \frac{L}{\eta_j} \frac{a_{31}x + a_{32}y + a_{33}z - a_{31}c_1 - a_{32}c_2 - a_{33}c_3}{a_{21}x + a_{22}y + a_{23}z - a_{21}c_1 - a_{22}c_2 - a_{23}c_3} + j_p \ , \tag{2}$$

where a_{ij} $(i,\ j = 1, 2, 3)$ are elements of matrix $\mathbf{R}$ which determines camera rotation in the world co-ordinates system. This matrix form is as follows:

$$\mathbf{R} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}, \tag{3}$$

where:

$$a_{11} = \cos(\varphi)\cos(\beta) + \sin(\varphi)\sin(\alpha)\sin(\beta)\,,$$

$$a_{12} = \sin(\varphi)\cos(\alpha)\,,$$

$$a_{13} = -\cos(\varphi)\sin(\beta) + \sin(\varphi)\sin(\alpha)\cos(\beta)\,,$$

$$a_{21} = -\sin(\varphi)\cos(\beta) + \cos(\varphi)\sin(\alpha)\sin(\beta)\,,$$

$$a_{22} = \cos(\varphi)\cos(\alpha)\,,$$

$$a_{23} = \sin(\varphi)\sin(\beta) + \cos(\varphi)\sin(\alpha)\cos(\beta)\,,$$

$$a_{31} = \cos(\alpha)\sin(\beta)\,,$$

$$a_{32} = -\sin(\alpha)\,,$$

$$a_{33} = \cos(\alpha)\cos(\beta)\,.$$

Equations (1) and (2) may be converted to the following form:

$$a'_{21}ix + a'_{22}iy + a'_{23}iz + B'_1x + B'_2y + B'_3z - B'_1c_1 - B'_2c_2 - B'_3c_3 = i\,, \tag{4}$$

$$a'_{21}jx + a'_{22}jy + a'_{23}jz + D'_1x + D'_2y + D'_3z - D'_1c_1 - D'_2c_2 - D'_3c_3 = j\,, \tag{5}$$

where:

$$a'_{2k} = \frac{a_{2k}}{A_2}\,, \qquad (k = 1, 2, 3) \tag{6}$$

$$B'_k = \frac{-La_{1k} - \eta_i i_p a_{2k}}{A_2 \eta_i}\,, \tag{7}$$

$$D'_k = \frac{-La_{3k} - \eta_j j_p a_{2k}}{A_2 \eta_j}\,, \tag{8}$$

$$A_2 = a_{21}c_1 + a_{22}c_2 + a_{23}c_3\,. \tag{9}$$

Let us introduce the following notation:

$(x_1, y_1, z_1), \ldots, (x_n, y_n, z_n)$ - the world co-ordinates of n landmarks;

$(i_1, j_1), \ldots, (i_n, j_n)$ - the projection co-ordinates of n landmarks.

The intrinsic camera parameters $(L, (i_p, j_p)$ and $(\eta_i, \eta_j))$ are supposed to be known. The relation between the world co-ordinates of n landmarks and projection co-ordinates of these n landmarks in one camera position can be expressed as the following matrix product:

$$\mathbf{N} \cdot \mathbf{g} = \mathbf{w}, \tag{10}$$

where:

$$\mathbf{N} = \begin{bmatrix} i_1x_1 & i_1y_1 & i_1z_1 & x_1 & y_1 & z_1 & 0 & 0 & 0 & -1 & 0 \\ i_2x_2 & i_2y_2 & i_2z_2 & x_2 & y_2 & z_2 & 0 & 0 & 0 & -1 & 0 \\ : & : & : & : & : & : & : & : & : & : & : \\ i_nx_n & i_ny_n & i_nz_n & x_n & y_n & z_n & 0 & 0 & 0 & -1 & 0 \\ j_1x_1 & j_1y_1 & j_1z_1 & 0 & 0 & 0 & x_1 & y_1 & z_1 & 0 & -1 \\ j_2x_2 & j_2y_2 & j_2z_2 & 0 & 0 & 0 & x_2 & y_2 & z_2 & 0 & -1 \\ : & : & : & : & : & : & : & : & : & : & : \\ j_nx_n & j_ny_n & j_nz_n & 0 & 0 & 0 & x_n & y_n & z_n & 0 & -1 \end{bmatrix}, \tag{11}$$

$$g = [\, a'_{21}, a'_{22}, a'_{23}, B'_1, B'_2, B'_3, D'_1, D'_2, D'_3, u'_1, u'_2 \,]^T, \tag{12}$$

$$u'_1 = B'_1 c_1 + B'_2 c_2 + B'_3 c_3, \tag{13}$$

$$u'_2 = D'_1 c_1 + D'_2 c_2 + D'_3 c_3, \tag{14}$$

$$w = [\, i_1, i_2, ..., i_n, j_1, j_2, ..., j_n \,]^T. \tag{15}$$

The elements of vector $\mathbf{g}$ depend on the camera parameters. The set of linear equations (10) will be solved using the least-squares techniques. The solution of the equation set (i.e. the vector $\mathbf{g}$), is a base to determine particular camera parameters as follows [5]:

- the camera translation vector **c** is a solution of the following equation set:

$$\begin{bmatrix} a'_{21} & a'_{22} & a'_{23} \\ B'_1 & B'_2 & B'_3 \\ D'_1 & D'_2 & D'_3 \end{bmatrix} \cdot \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} = \begin{bmatrix} 1 \\ u'_1 \\ u'_2 \end{bmatrix} \tag{16}$$

- camera rotation angles:

$$\beta = \operatorname{arctg}\left(-\frac{D_1' + j_p a_{21}'}{D_3' + j_p a_{23}'} \right), \tag{17}$$

$$\alpha = \operatorname{arctg}\left(-\frac{D_2' + j_p a_{22}'}{D_1' + j_p a_{21}'} \sin\beta \right), \tag{18}$$

$$\varphi = \operatorname{arctg}\left(\frac{\eta_i}{\eta_j} \frac{B_2' + i_p a_{22}'}{D_1' + j_p a_{21}'} \sin\beta \right). \tag{19}$$

3. Recursive filtration

Let us assume that the camera is stationary installed on a mobile robot. The robot navigation system will be a camera movement data source (i.e. translation vector $\mathbf{t} = (t_1, t_2, t_3)$ and rotation angles $\mathbf{\Delta} = (\Delta_\alpha, \Delta_\beta, \Delta_\varphi)$ describing camera pose change after one its move). It is convenient to handle a mobile camera as a linear dynamic system. In the calibration problem the intermediary parameters vector $\mathbf{g}(k)$ describes the state of the system in step k^{th}. Vector is not directly measurable, but the string of observed values $\mathbf{w}(1), \mathbf{w}(2), \ldots, \mathbf{w}(j)$ (i.e. projection co-ordinates of landmarks) is known. The observed values and vector $\mathbf{g}(k)$ are tied by a measurement system. The estimate of vector $\mathbf{g}(k)$ is searched. Current camera pose parameters (i.e. translation vector and rotation angles) are computed using the estimate according to formulas (16) - (19). This estimate in step k^{th} after j observations is denoted as $\hat{g}(k \mid j)$ and defined as an n-dimensional vector function ϕ_k:

$$\hat{g}(k \mid j) = \varphi_k(\mathbf{w}(1), \mathbf{w}(2), \ldots, \mathbf{w}(j)) \tag{20}$$

The estimation task will be solved for $k = j$ (such a task is called filtration). Probabilistic description of a state vector, noise vector, and a measurement error vector is unknown. In such a case the recursive filtration algorithm providing a minimum of output error is constructed. It is a filtration by least-square method. Algorithm for this dynamic system is described as following:

- state vector estimate

$$\hat{\mathbf{g}}(k+1 \mid k+1) = \mathbf{\Phi}(k+1, k)\, \hat{\mathbf{g}}(k \mid k) + \mathbf{K}(k+1)\,[\mathbf{w}(k+1) - \mathbf{N}(k+1)\, \mathbf{\Phi}(k+1, k)\, \hat{\mathbf{g}}(k \mid k)]; \tag{21}$$

- filter matrix

$$\mathbf{K}(k+1) = [\mathbf{Q}(k) + \mathbf{N}^T(k+1)\, \mathbf{N}(k+1)]^{-1} \mathbf{N}^T(k+1); \tag{22}$$

- matrix of weight factors (the knowledge accumulator)

$$\mathbf{Q}(k+1)=[\mathbf{\Phi}^{-1}(k+1,k)]^{T}\,[\mathbf{Q}(k)+\mathbf{N}^{T}(k+1)\,\mathbf{N}(k+1)]\,\mathbf{\Phi}^{-1}(k+1,k)\,; \tag{23}$$

- initial values $\hat{\mathbf{g}}(0\,|\,0)=\mathbf{0}$ and $\mathbf{Q}(0)=\mathbf{0}$.

Using the camera model, intrinsic camera parameters, currently estimated camera translation and rotation data, state vector $\mathbf{g}(k\,|\,k)$ and data from the navigation system (i.e. $\mathbf{t}=(t_1,t_2,t_3)$ and $\mathbf{\Delta}=(\Delta_\alpha,\Delta_\beta,\Delta_\varphi)$), the future state vector may be estimated with the following non-linear state equation:

$$g(k+1)=\mathbf{\Theta}[g(k),k]. \tag{24}$$

Equation (24) may be use as a basis to the following prediction:

$$\hat{\mathbf{g}}(k+1\,|\,k)=\Theta[\,\hat{\mathbf{g}}(k\,|\,k),k]. \tag{25}$$

For recursive filtration the state equation linearisation in each step is proposed. This idea will be accomplished by calculating the following transition matrix:

$$\mathbf{\Phi}(k+1,k)=\begin{bmatrix}\varphi_1(k) & 0 & \cdots & 0\\ 0 & \varphi_2(k) & \cdots & 0\\ \cdots & \cdots & \ddots & \cdots\\ 0 & 0 & \cdots & \varphi_n(k)\end{bmatrix}, \tag{26}$$

where

$$\varphi_i(k)=\frac{\hat{g}_i(k+1\,|\,k)}{\hat{g}_i(k\,|\,k)}. \tag{27}$$

4. Algorithm

The intermediate parameters vector $\mathbf{g}$ is estimated using recursive filtration procedure. The camera pose parameters (camera translation vector and rotation angles) are calculated using vector $\mathbf{g}$ and equations (16) - (19) for each step.

INTRINSIC CAMERA PARAMETERS (known and fixed during camera moving):

- distance between the camera optical centre O_c and image surface L;
- co-ordinates of the principal point (i_p,j_p);
- pixel size (η_i,η_j).

INPUT DATA (changeable for each camera position):

- world co-ordinates of n landmarks $(x_1,y_1,z_1),\ldots,(x_n,y_n,z_n)$;

- projection co-ordinates of landmarks $(i_{1,} j_1), \ldots, (i_{n,} j_n)$;
- translation vector $\mathbf{t} = (t_1, t_2, t_3)$ for each movement;
- rotation angles $\Delta = (\Delta_\alpha, \Delta_\beta, \Delta_\varphi)$ for each movement.

OUTPUT DATA:

- camera position vector (c_1, c_2, c_3);
- rotation angles (α, β, φ).

FILTRATION PROCEDURE:

1. World landmarks co-ordinates $(x_1, y_1, z_1), \ldots, (x_n, y_n, z_n)$ and projection landmarks co-ordinates $(i_{1,} j_1), \ldots, (i_{n,} j_n)$ acquisition for the initial position $k = 1$.
2. Matrix $\mathbf{N}$ and vector $\mathbf{w}$ evaluation according to formulas (11) and (15).
3. Initial vector $\mathbf{g}(k) = [g_1, g_2, \ldots, g_{11}]$ estimation by using the formula $\mathbf{g} := (\mathbf{N}^T\mathbf{N})^{-1}\mathbf{N}^T\mathbf{w}$.
4. Camera position vector $\mathbf{c}$ and rotation angles (α, β, φ) estimation for the initial position:

$$\begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} = \begin{bmatrix} g_1 & g_2 & g_3 \\ g_4 & g_5 & g_6 \\ g_7 & g_8 & g_9 \end{bmatrix}^{-1} \cdot \begin{bmatrix} 1 \\ g_{10} \\ g_{11} \end{bmatrix},$$

$$\beta = \arctan\left(-\frac{g_7 + j_p g_1}{g_9 + j_p g_3} \right),$$

$$\alpha = \arctan\left(-\frac{g_8 + j_p g_2}{g_7 + j_p g_1} \sin\beta \right),$$

$$\varphi = \arctan\left(\frac{\eta_i}{\eta_j} \frac{g_5 + j_p g_2}{g_7 + j_p g_1} \sin\beta \right).$$

5. Initialisation of the co-variance matrix $\mathbf{Q}$ by the formula $\mathbf{Q} := \mathbf{N}^T\mathbf{N}$.
6. Intermediate parameters prediction after the next camera movement in time k $k := k + 1$.
7. Camera movement data acquisition from navigation system (i.e. translation vector $\mathbf{t} = (t_1, t_2, t_3)$ and rotation angles $\Delta = (\Delta_\alpha, \Delta_\beta, \Delta_\varphi)$), the world co-ordinates of observed landmarks $(x_1, y_1, z_1), \ldots, (x_n, y_n, z_n)$ and the projection co-ordinates of observed landmarks $(i_{1,} j_1), \ldots, (i_{n,} j_n)$ in the current camera position.
8. Matrix $\mathbf{N}$ and vector $\mathbf{w}$ evaluation alike in the 2nd algorithm point.

9. Prediction $\breve{\mathbf{g}} = [\breve{g}_1, \breve{g}_2, \ldots, \breve{g}_{11}]$ evaluation based on the camera model through the following steps:
   - rotation angles estimation in current camera position:

     $(\alpha, \beta, \varphi) := (\alpha, \beta, \varphi) + (\Delta_\alpha, \Delta_\beta, \Delta_\varphi);$
   - rotation matrix $\mathbf{R}$ estimation according to formula (3);
   - translation vector estimation in current camera position $\mathbf{c} = \mathbf{R}^{-1} \cdot \mathbf{t} + \mathbf{c}$;
   - vector $\breve{\mathbf{g}}(k)$ estimation:

$$\breve{g}_1 := \frac{a_{21}}{\mathbf{c} \cdot (a_{21}, a_{22}, a_{23})^T}, \qquad \breve{g}_2 := \frac{a_{22}}{\mathbf{c} \cdot (a_{21}, a_{22}, a_{23})^T}, \qquad \breve{g}_3 := \frac{a_{23}}{\mathbf{c} \cdot (a_{21}, a_{22}, a_{23})^T},$$

$$\breve{g}_4 := \frac{-La_{11} - \eta_i i_p a_{21}}{\mathbf{c} \cdot (a_{21}, a_{22}, a_{23})^T \eta_i}, \qquad \breve{g}_5 := \frac{-La_{12} - \eta_i i_p a_{22}}{\mathbf{c} \cdot (a_{21}, a_{22}, a_{23})^T \eta_i}, \qquad \breve{g}_6 := \frac{-La_{13} - \eta_i i_p a_{23}}{\mathbf{c} \cdot (a_{21}, a_{22}, a_{23})^T \eta_i},$$

$$\breve{g}_7 := \frac{-La_{31} - \eta_j j_p a_{21}}{\mathbf{c} \cdot (a_{21}, a_{22}, a_{23})^T \eta_j}, \qquad \breve{g}_8 := \frac{-La_{32} - \eta_j j_p a_{22}}{\mathbf{c} \cdot (a_{21}, a_{22}, a_{23})^T \eta_j}, \qquad \breve{g}_9 := \frac{-La_{33} - \eta_j j_p a_{33}}{\mathbf{c} \cdot (a_{21}, a_{22}, a_{23})^T \eta_j},$$

$$\breve{g}_{10} := \mathbf{c} \cdot (\breve{g}_4, \breve{g}_5, \breve{g}_6)^T, \qquad \breve{g}_{11} := \mathbf{c} \cdot (\breve{g}_7, \breve{g}_8, \breve{g}_9)^T.$$

10. Evaluation of matrix $\mathbf{\Phi}$

$$\mathbf{\Phi} := \begin{bmatrix} \frac{\breve{g}_1}{g_1} & 0 & \cdots & 0 \\ 0 & \frac{\breve{g}_2}{g_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{\breve{g}_{11}}{g_{11}} \end{bmatrix}$$

11. Evaluation of matrix $\mathbf{K}$

$$\mathbf{K} := (\mathbf{Q} + \mathbf{N}^T \mathbf{N})^{-1} \mathbf{N}^T$$

12. Evaluation of estimator $\mathbf{g}$

$$\mathbf{g} := \breve{\mathbf{g}} + \mathbf{K} \cdot (\mathbf{w}^T - \mathbf{N} \cdot \breve{\mathbf{g}})$$

13. Evaluation of matrix $\mathbf{Q}$

$$\mathbf{Q} := \mathbf{\Phi}^{-1} (\mathbf{Q} + \mathbf{N}^T \mathbf{N}) \cdot \mathbf{\Phi}^{-1}$$

14. Current camera pose parameter estimation utilising vector $\mathbf{g}$ (alike in step 4).
15. If camera has not finished its movement then go to step 6.

5. Experiment description

In experiments the presented algorithm was tested in the following cases:

- medial number of the landmarks (i.e. 18) in initial frame and no less then 6 landmarks in subsequent frames;
- small number of the landmarks (i.e. 7) in initial frame and deficit or absence of landmarks in several subsequent frames;
- the robot navigation system data (i.e. vector (t_1, t_2, t_3) and vector $(\Delta_\alpha, \Delta_\beta, \Delta_\varphi)$) distorting.

The scenes were generated by a computer. In the first experiment 18 landmarks in initial frame and about 10 (but no less then 6) landmarks in subsequent were used. The exemplary projections of landmarks in the initial frame are showed in Figure 2. After 36 movements the sum of camera position changes was about 2.5m, and the sum of camera angle changes was about 2.5 rad. The calibration results were acceptable, the position error ≈ 2mm and the rotation error ≈ 0.002 rad. The graphs of calibration errors are showed in Figure 3.

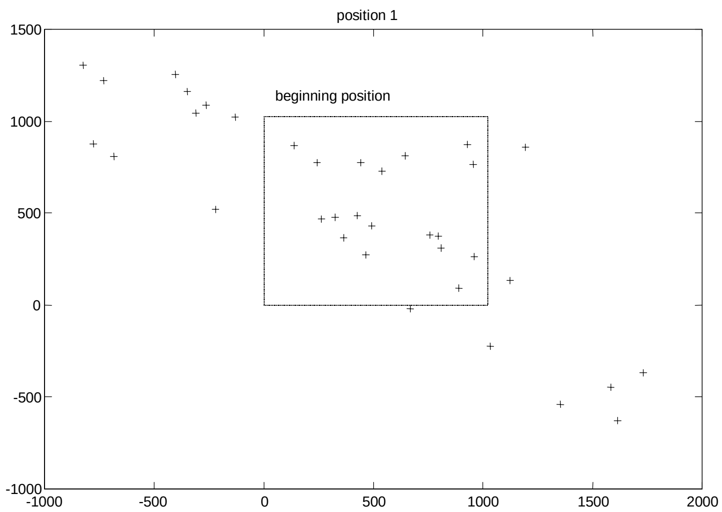

Figure 2. Landmarks projection for the camera beginning position

In the second experiment 7 landmarks in initial frame were used. In the fourth frame were no visible landmarks and in the eleventh frame only 3 landmarks were detected (for one-frame calibration method 6 landmarks are required). The landmarks projection in several subsequent camera positions as well as graphs of calibration errors are showed in Figure 4. The received results are acceptable.

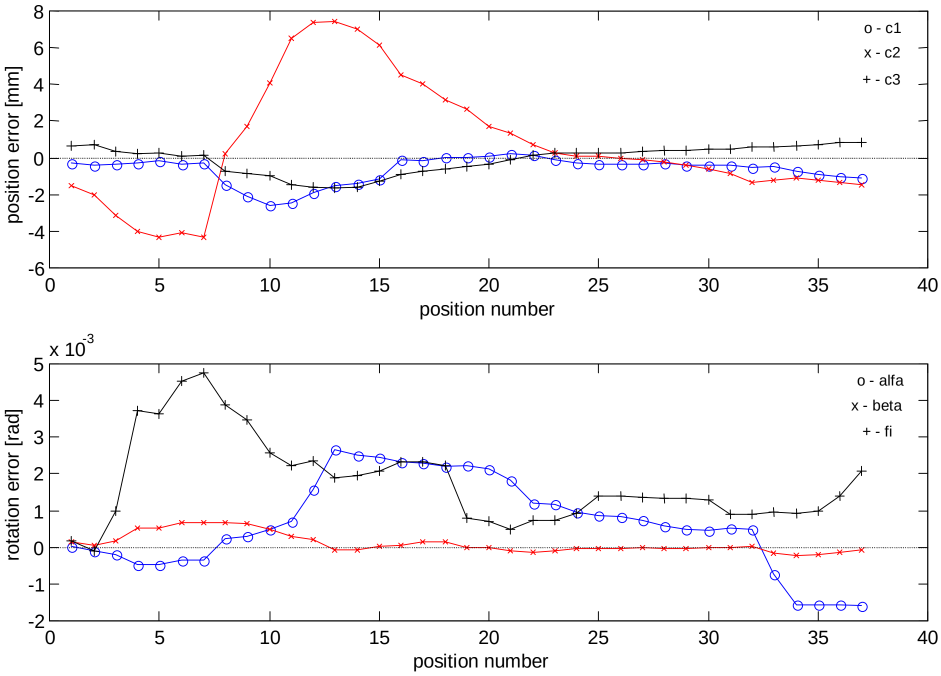

Figure 3. Calibration results for 36 movement

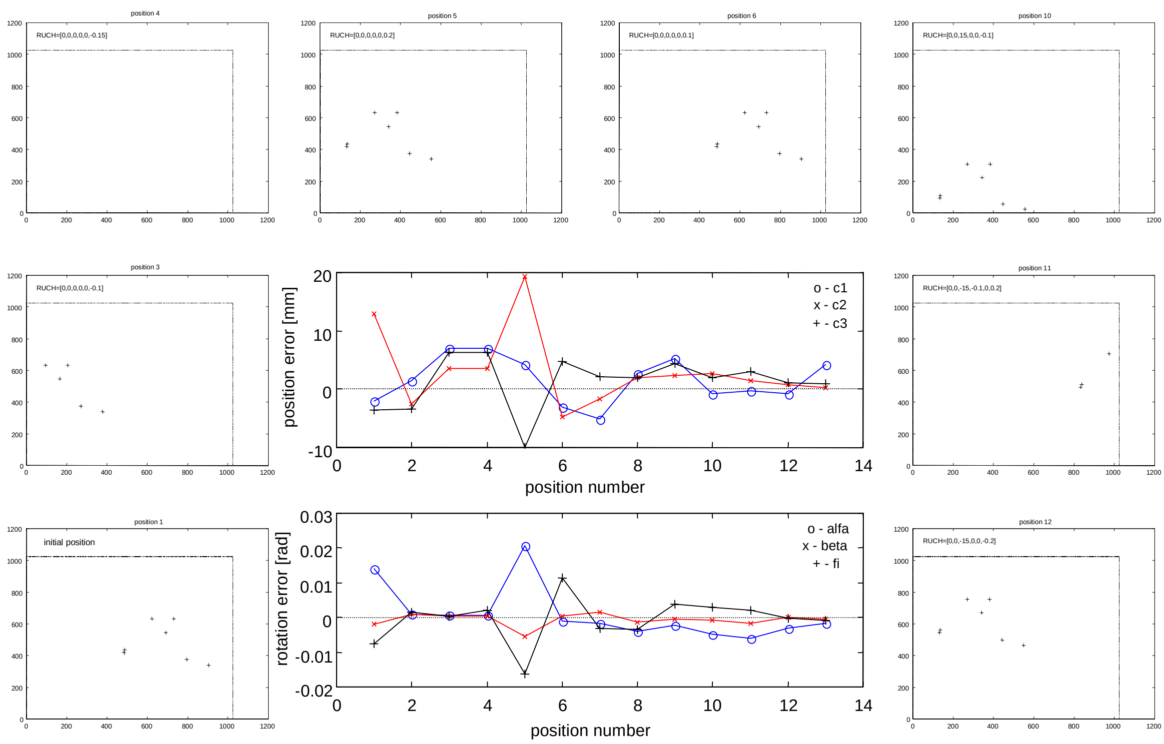

Figure 4. Calibration with deficit or absence of the landmarks in the frame (left top frame - no landmarks; right inner frame - 3 landmarks)

In the last experiment the algorithm sensitivity to distorting of the robot navigation system data was tested. The random errors were added to data acquired from the navigation system. Exemplary maximum error value for a movement was 20 mm and for a rotation was 0.2 rad (for instance, the precision of robot Nomad movement are 2.5mm for move and 0.0017 rad for rotation). After 48 movements the sum of camera position changes was about 4.8m and the sum of camera angle changes was about 2.5 rad. After the first several movements the errors were quite big (i.e. 4m and 0.3 rad respectively), but after 35 movements results were about 100 mm for position error and 0.01 rad for rotation error. The exemplary projections of landmarks in initial frame are showed in Figure 5, and the graphs of calibration errors are showed in Figure 6.

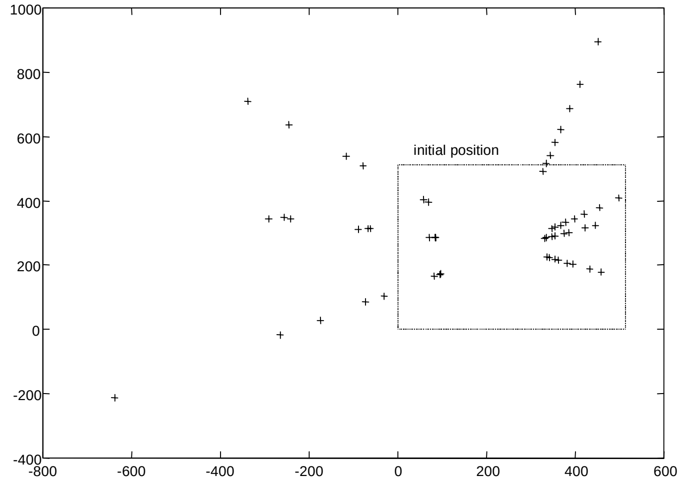

Figure 5. Filtration with distorted data -projections of landmarks in initial frame

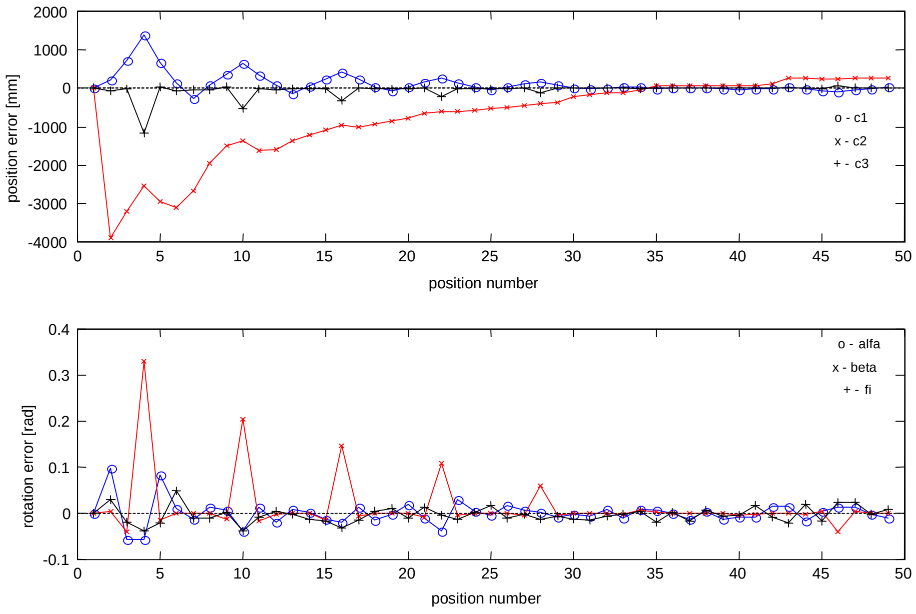

Figure 6. Filtration with distorted data - calibration results

Examinations of the algorithm confirm possibility of using this algorithm to determine pose of a mobile robot. Simply geometric camera model is fit to the space orientation procedures. For one-frame procedures no less then 6 landmarks are needed, but in the case of many frames acquired from a special way moved cameras 4 landmarks are good enough. A simply filtration method in connection with the robot navigation system data gives acceptable results even in the case of the landmarks deficit or absence in the several frames. However the full confirmation of this method usefulness can be obtained after experiment accomplishment in which the set of input data will be derived by a real camera.

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