Base Calibration for Dual Robot System

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Abstract: Calibration of the base coordinate systems of the two robot manipulators in a dual robot system has not received enough attentions, though its importance is obvious. This paper describes a base calibration method by taking advantage of a visual sensor held by one of the manipulators. This method is based on, but separated from the calibrations of the robot manipulators and the visual sensor themselves. Moreover, the algorithm proposed estimates the rotational and translational parameters with the help of the same set of instrumental variables, thus no errors propagate between them. Simulations are provided to show the properties of the mehod.

Key words: robot; dual-robot coordination; calibration; vision

1 Introduction

A dual robot system with visual or other sensors can be called a "compound robot system (CRS)" since it includes much more different interrelations inside. These interrelations between different parts of the system should be calibrated in order to build up the system model for control. Conventionally there have been two kinds of approaches for the calibrations of a CRS. One is the multi-step method. The other is the single-step method. In the early time, since the robot calibrations and sensor calibrations have already been studied extensively and many effective methods have been developed, calibrations of the CRS are often completed in multi-step methods. The whole system is divided into several layers. Each layer composes of several parts. Each part is calibrated by available calibration methods, which is simple and straightforward. But this kind of methods are inherently contaminated by error propagations from lower layers to higher ones. So the single-step methods are invented later which integrate all parts in a CRS into a unified frame by a single model^[1]. Error propagations can be overcome. But the system models are often nonlinear which require complex procedure for data acquisitions and parameter solutions.

Calibration is for control. It can be shown from control that the errors from different parts of a CRS may have different impacts on system control and system performance. This means that those who have greater impacts on system performance should be modelled more accurately. Furthermore, from the experience of calibration, it is shown that each part in a CRS may have its own characteristics in its model, which requires a specially designed solution for model estimation. So it is argued that for a CRS composed of robots and visual sensors, multi-step calibration methods are more suitable.

Base calibration, which is to calibrate the relations between the base coordinate systems of the two coordinated robots, is a peculiar and important problem in dual robot control. But

it has not received enough attentions. Literature [2] discussed a passive base calibration procedure for a dual robot system by using a series of "peg-into-hole" operations to set up the calibration equations as $AX = XB^{[3,4]}$. The final calibration accuracy depends on how precisely the peg aligned with the hole, which were monitored and adjusted manually based on force/torque sensory feedbacks.

In this paper, a new kind of vision-based calibration method for the base coordinate systems of a dual robot system is to be discussed. This method is implemented by the programmed shifts of one robot with their projections on the image plane observed by the camera fixed on the other one. Since the calibration algorithm relies on the calibrations of the robot and sensor themselves, its accuracy is limited to that of the robot and sensor parameters.

Details of the base calibration algorithm are to be described in Section 2. Since the solution can not ensure the estimated rotation matrix to be orthonormal as required by the transformations of the Cartesian coordinate systems, if there exist noises in data measurements, an orthonormalizing procedure is discussed in Section 3. Simulations are provided in Section 4, followed by the conclusions.

2 Vision-Based Calibration

Consider the two manipulators of a dual robot system. A visual sensor (camera) is fixed on one robot. This robot is from now on called "eye robot". A luminescence diode(LD) is adhered to another robot. This robot is called "hand robot". The LD is used to show a characteristic point of the eye robot in image plane. Define a set of coordinate systems system;

- B_e : the eye robot's base coordinate system;
- B_h : the hand robot's base coordinate system;
- C: the camera's coordinate system;
- \bullet G: the luminescence diode's coordinate system;

Then base calibration of the dual robot system is to determine the relations between B_e and B_h .

Supposing the calibrations of the kinematics of the two manipulators, calibrations of the camera model and the calibrations of the relations between the camera and the base of the eye robot have all been completed. The position of the LD with respect to the base of the hand robot are also known since its position is selected. This means the relations between C and B_{ϵ} and the relations between G and G are available at any time during the working procedure. Fixing the poses of the camera and LD, if the relations between the camera and the LD can be estimated, then the relations between the base coordinate systems can be computed consequently. Thus calibration of G_{ϵ} and G_{ϵ} are available at any specific poses of the two arms.

Calibration results vary with the camera and the LD located in different positions in robots' workspaces. Reasonable selections of the positions and poses of the camera and LD should be made before the calibration procedure begins. Literature [5] discussed the division of the workspace for robot system calibrations. Final result is often determined among candidates on applications. The following sections show the estimation of the relations between C

and G once the poses of the camera and the LD are settled down for calibration.

2.1 Preparations

Let C be a Cartesian coordinate system O_c -U-V-W, whose axes U, V are respectively parallel to the horizental and vertical grid lines of the camera image plane, and $W = U \times V$, Let G be another Cartesian coordinate system O_g -X-Y-Z, whose relations with B_h are known in advance. Then the relations between C and G can be expressed as:

$$C = {}^{c}R_{g}G + {}^{c}T_{g}$$

where ${}^cR_{g\;3\times3}$ is defined as the rotational matrix, and ${}^cT_{g\;3\times3}$ is the translational vector. cR_g and cT_g are the unknowns to be estimated for describing the relations between C and G.

For a line segment in the space with the length of L, its projection on the image plane is of the length l_n if it parallels to the axis U, and l_n if it parallels to V. From the pinhole model of the camera:

$$\begin{cases} l_u = f_u L/d, \\ l_v = f_v L/d, \end{cases}$$
 (1)

where f_u , f_v are respectively the weighted focal lengths by pixel scale factors in U, V directions, and d is the depth of the line segment, which means the distance between the line segment and the camera focus.

2. 2 Determination of ${}^{c}R_{e}$.

Define an instrumental coordinate system C':O'-U'-V'-W' with its origin O' coincided with G's origin O_g , and axes U', V' and W' parallel to C' s axes U, V' and W respectively. Supposing the angles between the axes X, Y, Z and the projection lines of X, Y, Z on U'-W' plane are respectively α_x , α_y and α_z and the angles between the axis U' and the projection lines of X, Y, Z on U'-W' plane are respectively β_x , β_y and β_z (see Fig. 1), then the rotation transformation matrix of the relations between C' and C' and C' are as as the matrix functions of the angles α_i and β_i , (i = x, y, z). Since the pose of the instrumental coordinate system C' is the same as that of C, the rotation transformation matrix C' from C' to C' which is:

$${}^{c}R_{g} = \begin{bmatrix} \cos\alpha_{x}\cos\beta_{x} & \cos\alpha_{y}\cos\beta_{y} & \cos\alpha_{z}\cos\beta_{z} \\ \sin\alpha_{x} & \sin\alpha_{y} & \sin\alpha_{z} \\ \cos\alpha_{x}\sin\beta_{x} & \cos\alpha_{y}\sin\beta_{y} & \cos\alpha_{z}\sin\beta_{z} \end{bmatrix}. \tag{2}$$

Let the origin O_g of the hand coordinate system G shift along its axes' directions X,Y,Z respectively with distance L, the shifts projections on image plane in U,V directions can be observed as u_x, v_x, u_y, v_y and u_z, v_z respectively, which are known from image processing. Assuming the variance of the depth of O_g with respect to the image plane due to the shifts can be ignored compared with the depth d itself, the following equations are straightforward from camera pinhole model:

$$\begin{cases} u_x = f_u L \cos \alpha_x \cos \beta_x / d, & v_x = f_v L \sin \alpha_x / d, \\ u_y = f_u L \cos \alpha_y \cos \beta_y / d, & v_y = f_v L \sin \alpha_y / d, \\ u_z = f_u L \cos \alpha_z \cos \beta_z / d, & v_z = f_v L \sin \alpha_z / d. \end{cases}$$
(3)

Substituting (1) into (3) leads to:

$$\begin{cases} u_x = l_u \cos \alpha_x \cos \beta_x, & v_x = l_v \sin \alpha_x, \\ u_y = l_u \cos \alpha_y \cos \beta_y, & v_y = l_v \sin \alpha_y, \\ u_z = l_u \cos \alpha_z \cos \beta_z, & v_z = l_v \sin \alpha_z. \end{cases}$$

$$(4)$$

From (4) and (2), ${}^{c}R_{g}$ can be transformed to be the functions of l_{u} and l_{v} . So the following paragraphs are devoted to the solutions of l_{u} and l_{v} .

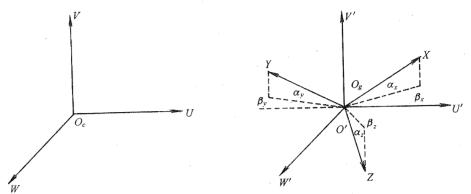


Fig. 1 Sketch of the camera and LD coordinate systems

The relations of the angles depicted in Fig. 1 can be described as:

$$\begin{cases} \cos^2 \alpha_x \cos^2 \beta_x + \cos^2 \alpha_y \cos^2 \beta_y + \cos^2 \alpha_z \cos^2 \beta_z = 1, \\ \sin^2 \alpha_x + \sin^2 \alpha_y + \sin^2 \alpha_z = 1. \end{cases}$$
 (5)

In addition, equation (1) means:

$$\frac{l_u}{l_v} = \frac{f_u}{f_v}. (6)$$

Combining equations (4) \sim (6), l_u and l_v can be solved out:

$$l_{u} = \sqrt{u_{x}^{2} + u_{y}^{2} + u_{z}^{2}}, \quad l_{v} = \sqrt{v_{x}^{2} + v_{y}^{2} + v_{z}^{2}}.$$
 (7)

Substituting Eq. (7) into (2), cR_s can then be solved out:

$${}^{c}R_{g} = \begin{bmatrix} k_{1} & k_{2} & k_{3} \end{bmatrix}^{T},$$
 (8)

where

$$k_1 = \left[rac{u_x}{l_u} \quad rac{u_y}{l_u} \quad rac{u_z}{l_u}
ight]^{ ext{T}}, \quad k_2 = \left[rac{v_x}{l_v} \quad rac{v_y}{l_v} \quad rac{v_z}{l_v}
ight]^{ ext{T}}, \quad k_3 = k_1 imes k_2.$$

2. 3 Determination of $^c T_g$

The translational transformation vector T_g relating G to C can also be determined using the instrumental parameters l_u and l_v estimated above. If the position of O_g observed on the image plane is (u_g, v_g) , then the translational vector $T_g = [t_x, t_y, t_z]^T$ can be computed by:

$$\begin{cases} t_{x} = u_{g}L(\frac{1}{l_{u}} + \frac{f_{v}}{l_{v}f_{u}})/2, \\ t_{y} = v_{g}L(\frac{1}{l_{v}} + \frac{f_{u}}{l_{u}f_{v}})/2, \\ t_{z} = L(\frac{f_{u}}{l_{u}} + \frac{f_{v}}{l_{v}})/2. \end{cases}$$
(9)

Equations (8) and (9) show that the solutions of cR_g and cT_g are all dependent on l_u and l_v , i.e. the accuracy of l_u and l_v affect the accuracy of cR_g and cT_g simultaneously, which means

no error propagations exist between them.

2. 4 Computations of the Base Relations

Up to here, the relations between the camera and the LD coordinate systems, ${}^{c}R_{g}$ and ${}^{c}T_{g}$, have been estimated. Thus the relations between the base coordinate systems, ${}^{B_{c}}R_{B_{h}}$ and ${}^{B_{c}}T_{B_{h}}$, can be computed from ${}^{c}R_{g}$, ${}^{c}T_{g}$, with the help of the relations of the camera and LD with their host robot manipulators:

$$\begin{cases}
{}^{B_{e}}R_{B_{h}} = {}^{B_{e}}R_{c}{}^{c} R_{g}{}^{B_{h}} R_{g}^{-1}, \\
{}^{B_{e}}T_{B_{h}} = -{}^{B_{e}}R_{B_{h}}{}^{B_{h}}T_{g} + {}^{B_{e}}R_{c}{}^{c} T_{g} + {}^{B_{e}}T_{c}
\end{cases} (10)$$

where ${}^{i}R_{j}$ is the rotational matrix from coordinate system j to i, and ${}^{i}T_{j}$ is the translational vector. Since the relations between the robot manipulators and the camera and the LD are all calibrated in advance, these relations are available from inner sensors.

The calibration procedures stated above are usually done several times by setting the camera and LD at different positions in different poses in robots' workspaces. Thus several estimations of ${}^{c}R_{g}$ and ${}^{c}T_{g}$ can be obtained, which mean several estimations of ${}^{B_{e}}R_{B_{h}}$ and ${}^{B_{e}}T_{B_{h}}$ for different sub-workspaces of the robot manipulators. Selections of the final results are due to applications.

3 Orthonormalization of the Rotation Matrix

Theoretically the rotation transformation matrix between Cartesian coordinate systems must be orthonormal. But this characteristics can not be ensured by (8) for cR_g if there exist system modeling errors and measurement noises. Thus an orthonormalizing procedure is necessary to adjust the three row (or column) vectors in cR_g .

For a coordinate system whose axes are not perpendicular to each other, it is easier to adjust two of the three axes with the remain one being the datum axis. Obviously this strategy leads to less reasonable modifications compared with that of adjusting three axes simultaneously.

The basic idea adopted here for the axes' adjustment is that the modifications of the axes to be orthogonal must be the least. So define a cost function J:

$$J = \|r_1 - k_1\|^2 + \|r_2 - k_2\|^2 + \|r_3 - k_3\|^2, \tag{11}$$

where $k_i (i = 1,2,3)$ is the transpose of the *i*-th row vector of R_g , and $r_i (i = 1,2,3)$ is the axis vector of a Cartesian coordinate system nearest to k_i . Obviously, the following equations stand for $r_i (i = 1,2,3)$ from their orthonormality:

$$r_1 \times r_2 = r_3, \quad r_1 \cdot r_2 = 0$$
 (12)

and

d

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$$||r_1||^2 = 1, ||r_2||^2 = 1.$$
 (13)

Substituting (12) into (11) and using the Lagrangian operators to take into account the constraint of (13):

$$J = ||r_{1} - k_{1}||^{2} + ||r_{2} - k_{2}||^{2} + ||r_{1} \times r_{2} - k_{3}||^{2} + \lambda_{1}r_{1} \cdot r_{2} + \lambda_{2}(||r_{1}||^{2} - 1) + \lambda_{3}(||r_{2}||^{2} - 1).$$

$$(14)$$

To solve out r_1 and r_2 , minimizing the function J with respect to $r_i (i=1,2)$, and $\lambda_i (i=1,2)$

2,3):

$$\frac{\partial J}{\partial r_i} = 0, \quad \frac{\partial J}{\partial \lambda_i} = 0 \tag{15}$$

which leads to the following nonlinear equations:

e following nonlinear equations:
$$\begin{cases}
r_{1} - k_{1} + \frac{\partial(r_{1} \times r_{2})}{\partial r_{1}}(r_{1} \times r_{2} - k_{3}) + \frac{\lambda_{1}}{2}r_{2} + \lambda_{2}r_{1} = 0, \\
r_{2} - k_{2} + \frac{\partial(r_{1} \times r_{2})}{\partial r_{2}}(r_{1} \times r_{2} - k_{3}) + \frac{\lambda_{1}}{2}r_{1} + \lambda_{3}r_{2} = 0, \\
r_{1} \cdot r_{2} = 0, \\
\parallel r_{1} \parallel^{2} - 1 = 0, \\
\parallel r_{2} \parallel^{2} - 1 = 0.
\end{cases} (16)$$

There are nine independent equations in (16) for nine unknowns (3 in r_1 , 3 in r_2 , and λ_1 , λ_2,λ_3). So (16) are solvable. An iterative procedure must then be used to reach the solutions.

The new orthonormalized rotation matrix for cR_g is $[r_1 \quad r_2 \quad r_1 \times r_2]^T$.

Simulations 4

A true experimental testpad is modelled as the simulation environment used to verify the algorithms stated above. The relations between the camera and the eye robot base are:

$${}^{B_{e}}R_{e}=egin{bmatrix} 0 & 0 & 1 \ -1 & 0 & 0 \ 0 & -1 & 0 \end{bmatrix}, \quad {}^{B_{e}}T_{e}=egin{bmatrix} 0 & 5 \ 0 & 1 \ 1 \end{bmatrix},$$

and the relations between the LD and the hand robot base are:

$${}^{B_h}R_g = \left[egin{array}{cccc} 0 & 0 & 1 \ 0 & 1 & 0 \ -1 & 0 & 0 \end{array}
ight], \quad {}^{B_h}T_g = \left[egin{array}{cccc} 0.6 \ -0.2 \ 1.1 \end{array}
ight].$$

The relations between the bases of the two robots obtained by the method stated in [3] are:

$$^{B_{e}}R_{B_{h}} = \begin{bmatrix} -0.9550 & -0.0296 & -0.2950 \\ 0.0298 & -0.9995 & 0.0041 \\ -0.2950 & -0.0049 & 0.9555 \end{bmatrix}, \quad ^{B_{e}}T_{B_{h}} = \begin{bmatrix} 5 \\ -0.1 \\ 0.1 \end{bmatrix}$$

which are assumed to be the true values. And the camera's normalized focal lengths, $f_{\it u}$ and f_v , are set to be 1017. 3 and 979. 5 respectively, which are the calibrated values of a camera in our laboratory.

Let the LD move 0.01 unitlength along its three axes respectively. The algorithms described in section 2 give the results as:

$${}^{\circ}R_{\mathrm{g}} = \begin{bmatrix} 0.0059 & 0.9993 & -0.0358 \\ 0.9531 & 0.0051 & 0.3025 \\ 0.3025 & -0.0359 & -0.9525 \end{bmatrix}, \quad {}^{\circ}T_{\mathrm{g}} = \begin{bmatrix} -0.0223 \\ 0.0250 \\ 3.6084 \end{bmatrix}.$$

Thus by the Eq. (10), ${}^{B_e}R_{B_h}$ and ${}^{B_e}T_{B_h}$ can be computed:

$${}^{B_{c}}R_{B_{h}} = \begin{bmatrix} -0.9525 & -0.0359 & -0.3025 \\ 0.0358 & -0.9993 & 0.0060 \\ -0.3025 & -0.0052 & 0.9531 \end{bmatrix}, \quad {}^{B_{c}}T_{B_{h}} = \begin{bmatrix} 5.0055 \\ -0.1056 \\ 0.1071 \end{bmatrix}.$$

It can be validated that, without measurement noises, ${}^{c}R_{g}$, thus ${}^{B}{}_{c}R_{B_{b}}$, is orthonormal.

If the measurements of the LD positions in the image plane involve noises, then ${}^{c}R_{\varepsilon}$ (thus ${}^{B_{\varepsilon}}R_{B_{h}}$) may not be of orthonormality. The Gaussian white noises of the magnitude of 1% and 5% are introduced to simulate the data errors. System configurations are set the same as above. Table 1 lists the estimated results.

Table 1 Estimated relations of C and G with noises

		1% noise			5% noise	
	-0.0398	0.9957	−0. 0833	-0.2224	0.9743	-0.0349
cR_g	0.9435	0.0047	0.3313	0.9526	0.0037	0.3043
	0.3303	-0.0654	-0.9397	0.2966	0.0344	-0.9290
T_g	-0.0221	0.0248	3. 6178	-0.0216	0.0243	3. 6889

It is easily checked that cR_g in Table 1 is not orthonormal in the existance of noises. So it should be adjusted to be orthonormal with the orthonormalization procedure discussed in section 3. Assigning each row vector of cR_g in Table 1 to $k_i (i=1,2,3)$, and solving Eq. (16) by the Optimization Toolbox from MATLAB, cR_g can be orthonormalized to cR_g is Table 2.

Table 2 Orthonormalized ${}^{c}R_{g}$ in Tab. 1

	1% noise			5% noise		
	-0.0113	0.9972	-0.0734	-0.1190	0.9929	-0.0012
${}^{c}R_{g}{}^{or}$	0.9436	0.0349	0.3292	0.9452	0.1137	0.3060
	0.3309	-0.0655	-0.9414	0.3040	0.0353	-0.9520

Thus ${}^{B_e}R_{B_h}$ and ${}^{B_e}T_{B_h}$ can be computed from Eq. (10) by replacing ${}^{c}R_{g}$ with ${}^{c}R_{g}{}^{or}$. The results are shown in Tab. 3. From Tab. 3, it can easily be seen that the matrix ${}^{B_e}R_{B_h}$ is surely orthonormal.

Table 3 Estimated ${}^{B_e}R_{B_h}$ and ${}^{B_e}T_{B_h}$ with noises

***************************************	1% noise			5% noise		
	-0.9414	-0.0655	-0.3309	-0.9520	0.0353	-0.3040
$^{B_e}R_{B_h}$	0.0734	-0.9972	-0.0113	0.0012	-0.9929	-0.1190
	-0.3292	-0.0349	0.9436	-0.3060	-0.1137	0.9425
$B_e T_{B_h}$	5.0334	-0.1089	0.1278	5. 1015	0.0533	0.0969

An alternative is that ${}^{B_c}\dot{R}_{B_h}$ can firstly be computed from cR_g instead of ${}^cR_g{}^{or}$, and then adjust ${}^{B_c}R_{B_h}$ to be orthonormal with the orthonormalizing procedure. Simulations show that this scheme leads to lower accuracy than the scheme adopted above.

5 Conclusions

A new calibration method based on visual feedbacks has been presented for dual robot base coordinate systems. This method is a part of a multi-step calibration method for a compound robot system, which prerequires the robot calibrations and the sensor calibrations. So

the final accuracy may be affected by error propagations. An orthonormalizing adjustment is also given to the calibrated rotation matrix to guarantee its orthonormality, especially in the existence of measurement noises.

It is argued that from the calibration point of view, the model of each part in a CRS may have its own peculiar characteristics for calibrations. Thus a specially designed calibration method may get more accurate model. Moreover, since the calibration is for control. From the control point of view, different parts in a CRS may have different impacts on system control and system performance. So those who have more affects on system control deserve finer calibrations to obtain more accurate models. All these can only be implemented by multi-step calibrations.

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双机器人系统的基坐标系标定

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摘要:多机器人协调系统研究中,机器人基坐标系之间的关系标定是一个重要而困难的问题,本文研究一种基于视觉传感的双机器人基坐标系关系的标定方法,通过一个机械手持有的摄像机观察另一个机械手末端的主动运动来实现.该方法独立于机器人系统中的其它关系的标定过程,可由系统自动完成,且不需要任何人工标定辅助.文中还给出了消除标定误差的直角坐标系坐标轴正交归一化的方法.仿真研究表明所给方法的有效性.

关键词: 机器人; 双机器人协调; 标定; 视觉

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