Kinematic Calibration and Vision-Based Object Grasping for Baxter Robot

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Abstract. In this paper, firstly, we analyze and compare four robot kinematic calibration methods for Baxter robot, including screw-axis measurement, extended kalman filtering, least squares method, integration of screw-axis measurement and kalman filtering. The performance of these four methods are evaluated through an experiment. Secondly, we analyze the monocular-vision and binocular-vision in object grasping, and propose a vision-based step-by-step object grasping strategy for the Baxter robot to grasp an object. Experiment results show that the object can be grasped based on the proposed method.

Keywords: Kinematic calibration · Vision-based object grasping · Baxter robot

1 Introduction

Since the dual arm robot can complete some tasks like human being, it has been focused by many researchers [1]. Many dual arm robots, such as SDA 10 [2], PR2 [3], Baxter [4], have been developed for varied applications. Bater robot is an industrial robot with two arms and two cameras on the arms, which has been applied in many applications, especial in picking tasks [4]. To complete the picking tasks, it is necessary to improve the positioning accuracy and grasp the object accurately.

There are many ways to improve the accuracy of positioning and object grasping for the robot. Calibration of the geometric parameters of the robot and sensor-based object grasping are the common methods, which received focuses by the researchers. Normally, the calibration of geometric parameters can be realized through the following four steps: modelling, measurement, parameter identification, and error compensation [5]. Homogeneous transformation matrix based D-H model is the usual model used for calibration [6]. However, the kinematic singularity occurs when using such D-H model. To overcome the kinematic singularity, some revised D-H model were proposed in [7–9]. Some studies realized the calibration of robot based on laser tracking [10] or CMM [11]. Such methods can obtain high accuracy, but with high economic cost. For parameter identification, Kalman filtering [12], and Maximum

N. Kubota et al. (Eds.): ICIRA 2016, Part I, LNAI 9834, pp. 269–278, 2016.
DOI: 10.1007/978-3-319-43506-0_23

likelihood method [13] are the common ways. Due to the advantages of vision sensors, the vision-based object grasping has been focused by many researchers [14–16]. In [14], a vision-based method was proposed to estimate the pose of the object. While in [15], a monocular vision-based 6D object localization method was proposed to realize the intelligent grasping. In [16], a fast algorithm for object detection using Scale Invariant Features Transform keypoint detector was proposed for a manipulator to detect and grasp an object. The methods for robot kinematic calibration and object grasping described above can used for some robots with high stiffness. However, they are difficult to be used for the robots with low stiffness, such as Baxter robot.

In this paper, we aim to propose methods to realize the kinematic calibration and object grasping for Baxter robot. We compare four methods in the kinematic calibration for Baxter robot, including the integration of screw-axis measurement and kalman filtering, screw-axis measurement, least square method, and extended kalman filtering. We also compare the monocular vision and the binocular vision, and propose a step by step object grasping method for the Baxter robot grasps an object. The proposed methods are evaluated through experiments with the laser tracker.

The problem is formulated in Sect. 2. The proposed method is described in Sect. 3. The experiments and discussions are presented in Sect. 4, and the conclusion is presented in Sect. 5.

2 Problem Formulation

In this paper, we take the Baxter robot as the research object. Baxter robot a dual-arm robot, which is developed based on the Robot Operating System (ROS) [4]. There are 7-DOF in each arm. Unified Robot Description Format (URDF) file is used to describe the kinematic model of the Baxter robot. The next frame is obtained by the transformation of previous frame in the three coordinate axis. The frame of the Baxter's arm is shown in Fig. 1. The kinematic model of Baxter robot can be described as follow:

$$ {}^{base}_{gripper}\boldsymbol{T} = {}^{base}_{1}\boldsymbol{T}\,{}^{1}_{2}\boldsymbol{T} \cdots {}^{7}_{gripper}\boldsymbol{T} \quad (1) $$

According to the definition of URDF, the frame transformation between two adjacent frames can be described as follow:

$$ {}^{i}_{i+1}\boldsymbol{T} = \boldsymbol{R}_z(\boldsymbol{\theta}_i)\boldsymbol{T}_{xyz}\left(\boldsymbol{P}_i\right)\boldsymbol{R}_z\left(\boldsymbol{\alpha}_{iz}\right)\boldsymbol{R}_y\left(\boldsymbol{\alpha}_{iy}\right)\boldsymbol{R}_x\left(\boldsymbol{\alpha}_{ix}\right) \quad (2) $$

Here, $\boldsymbol{R}_{\mathbf{a}}$ is the rotation matrix around a axis, $\boldsymbol{T}_{\mathbf{a}}$ is the translation matrix along a axis. α_{ix}, α_{iy}, α_{iz} and $\boldsymbol{P}_{\boldsymbol{i}}$ are the orientation and position of the link i, respectively. θ_i is the rotation angle of joint i.

There are many parameters in the frame transformation, it is difficult to identify these parameters. According to the specification of Baxter robot [4], to obtain the accurate kinematic model, we need calibrate 38 parameters including 14 orientation parameters and 24 position parameters. We compare four methods in the identification of parameters for Baxter robot.

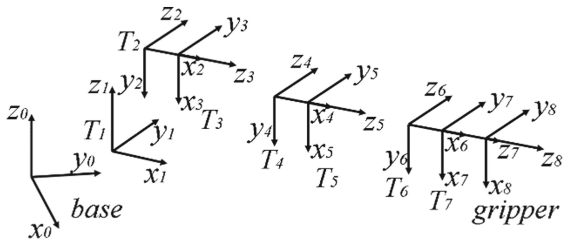


Fig. 1. The frames of Baxter's arm

To grasp an object accurately, the object should be positioned accurately. The eye-in-hand system is usually used in a robotic system to grasp an object due to its flexibility. Because a camera is attached on each arm for the Baxter robot, we can consider the system as an eye-in-hand system. We analyze the monocular vision and the binocular vision in the object grasping.

3 Proposed Method

3.1 Robot Kinematic Calibration

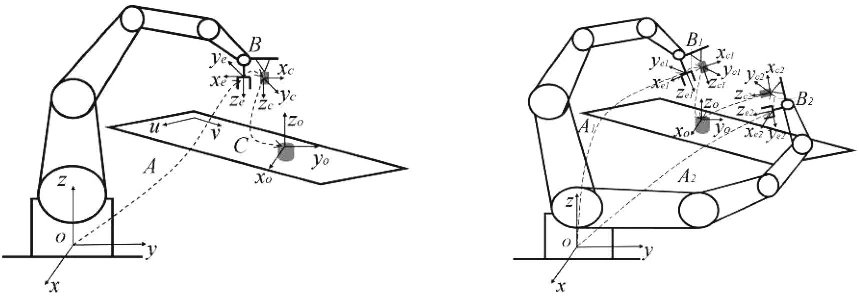
We compare the screw-axis measurement, extended kalman filtering, integration of screw-axis measurement and kalman filtering, and least square method. Following, we will describe these four methods simply.

Screw-axis measurement (SAM) is a way to calibrate the kinematic of robots [17]. When using screw-axis measurement, only one joint is moving, while other joints are motionless. The trajectory of a point on the moving joint is measured to obtain the position and orientation of the joint, which is used to calculate the kinematic parameters. The details of screw-axis measurement can be found in [17, 18].

Calman filtering (KF) is a way of linear quadratic estimation, which has been used to estimate the kinematic parameters of robots [19]. The extended calman filtering (EKF) is also used to estimate the kinematic parameters of robot [13, 20], which is considered as an optimization algorithm. The least square method (LSM) is a standard approach in regression analysis to the approximate solution of overdetermined systems, which has been used in the estimation of kinematic parameters for the robots [21]. To evaluate the previous system identification methods in the kinematic calibration of Baxter, we apply the EKF, LSM, and SAM in the kinematic calibration, including the position and orientation. We integrate the SAM and KF by using the SAM to estimate the orientation parameters and using the KF to estimate the position parameters. The details of KF can be referred to reference [19], and the details of EKF can be referred to reference [13].

3.2 Vision-Based Object Grasping

The coordinate frames for the monocular-vision and the binocular-vision are shown in Fig. 2(a) and (b), respectively. A, B, C are the robot base frame, end-effector frame, and camera frame, respectively. Normally, the grasped object is put on a flat. For the monocular-vision system, the robot should move to the upper of the flat, and make the optic axis of the camera be vertical to the flat. The positioning accuracy of monocular-vision depends on the verticality between the optic axis of the camera and the flat, and the calibration of the camera. When the working environment change, the calibration of the camera should be done once again. While using the binocular-vision, the flexibility and adaptability to the environment are improved, the matching points for these two cameras should be matched accurately.



(a) Monocular-vision (b) Binocular-vision

Fig. 2. Coordinate frames for eye-in-hand robot system

Whether using monocular-vision or binocular-vision, the positioning error exists in the real application. In this paper, we propose a step-by-step object grasping strategy. First, we move the robot to the approximate position based on binocular-vision, and then calculate the position error $\Delta X = (e_x, e_y, e_z, 0, 0, 0)^{\mathrm{T}}$ between the position of object and the current position of the end-effector. Because the position error is normally small, we can calculate the change of joints when compensating the position error based on the following equation:

$$\Delta\theta = J^{-1}\Delta X \tag{3}$$

Here, J is the Jaccobian matrix.

The implementation of step-by-step strategy in the object grasping is shown in Fig. 3. The object is grasped through two steps.

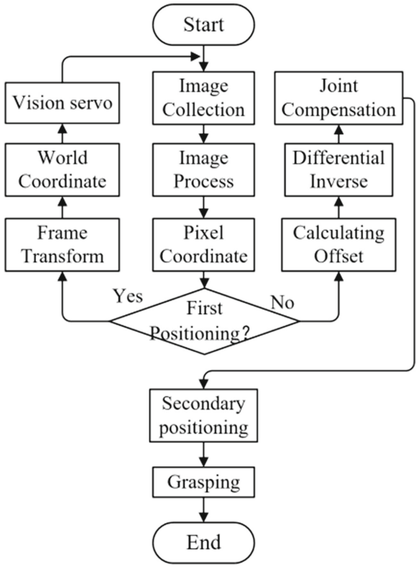


Fig. 3. Implementation of step-by-step strategy in object grasping

4 Experiment, Result and Discussion

4.1 Experiment for Kinematic Calibration

We evaluate the four robot kinematic calibration methods through an experiment with a laser tracker, as shown in Fig. 4. The measurement accuracy of the laser tracker is (10 + 5L) um, L is the measurement distance. In this paper, we set L to 2 m. Therefore, the measurement accuracy of the laser tracker is 20 um. 150 points in the workspace of the robot are set to the measure points.

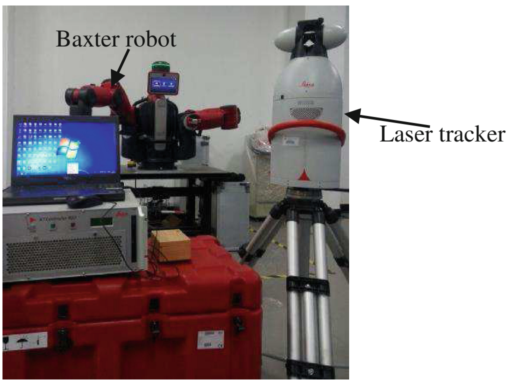


Fig. 4. Experiment setting in the evaluation of kinematic calibration methods

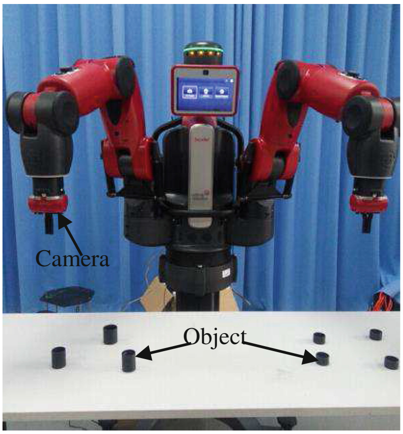
Table 1. The position error before and after calibration (unit mm)

Positioning error	No calibration	EKF	SAM	LSM	SAM + KF
Mean error	14.21	16.11	18.46	13.43	6.26
Standard deviation	5.39	10.78	6.21	4.96	3.22

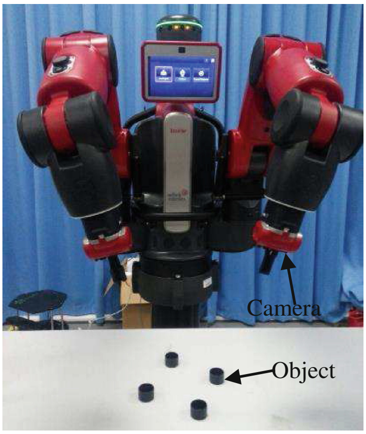
The positioning error is the distance between the position measured by the laser tracker and the position of goal point. The positioning error before calibration and after calibration is shown in Table 1. Before calibration, i.e., the values of kinematic parameters are given based on the nominal model, the mean of positioning error is 14.21 mm. This is because the stiffness of the joint for the Baxter robot is low, which affect the positioning accuracy of the robot. By using the EKF, SAM, and LSM to calibrate the kinematic parameters, the positioning error is 16.11 mm, 18.46 mm, and 13.43 mm, respectively. The positioning error cannot be reduced after the calibration by using the EKF, SAM, and LSM. When using the EKF, it is difficult to adjust the covariance matrix of measurement, which may affect the convergence of the EKF. By using the SAM, the accuracy of the screw-axis equation is important to reduce the positioning error. However, it is difficult to obtain the accurate equation due to the low stiffness of the Baxter robot. The LSM is sensitive to the measure error, which will affect the effectiveness of the calibration. By using the SAM + KF, the positioning error is 6.26 mm, which is smaller than that based on the nominal model. This is because the SAM can calibrate the orientation parameter and the KF can calibrate the position parameter well.

4.2 Experiment for Object Grasping

In this experiment, we first analyze the measure error by using the monocular-vision and the binocular-vision, and then test the step-by-step strategy for object grasping. The experiment settings for monocular-vision and binocular-vision are shown



(a) Monocular-vision



(b) Binocular-vision

Fig. 5. Experiment setting

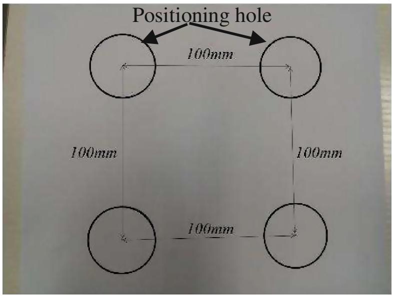
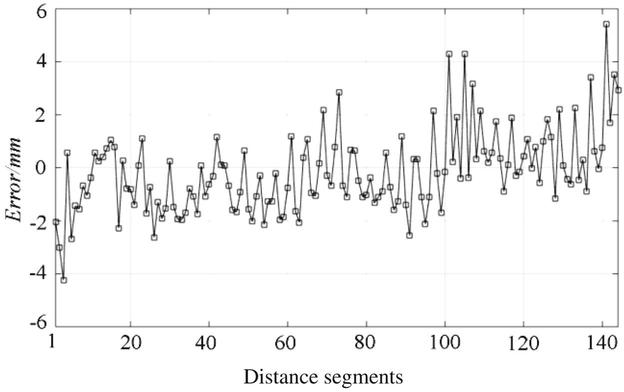
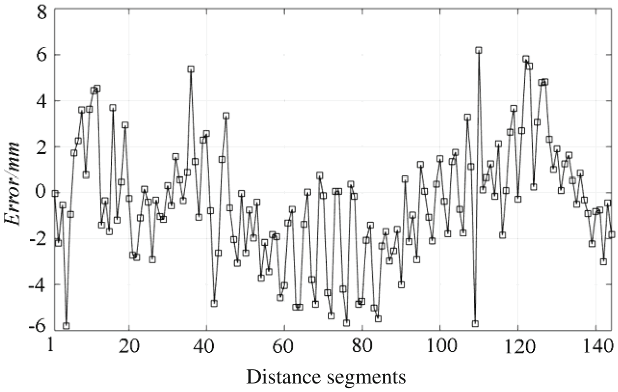


Fig. 6. Positioning plate



(a) Measure error derived by monocular-vision



(b) Measure error derived by binocular-vision

Fig. 7. Measure error derived by monocular-vision and binocular-vision

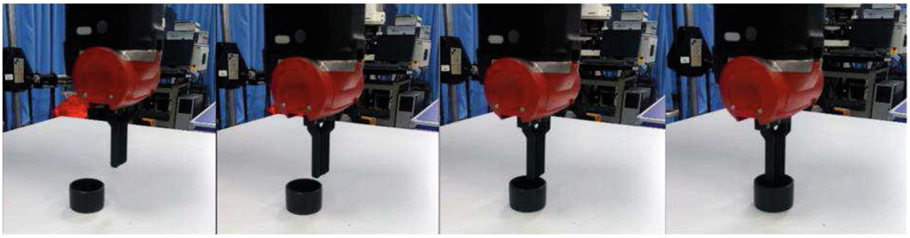


Fig. 8. Process of object grasping

in Fig. 5(a) and (b). We capture the image for a positioning plate, which has four holes on the plate. There are four distance segments on one plate. The length of each distance segment between the adjacent holes is 100 mm, as shown in Fig. 6. The measure error is the difference between the real length of the distance segment and the length measured by the camera. We put the plate in different positions on the table with different orientation, and test total measure 144 pieces of distance segments.

The measure errors derived by monocular-vision and binocular-vision are shown in Fig. 7(a) and (b). The mean of the measure error derived by the monocular-vision is 1.20 mm, while the mean of the measure error derived by the binocular-vision is 2.07 mm. The mean of the measure error derived by the monocular-vision is smaller than that derived by the binocular-vision. This is because the binocular-vision is affected by the accuracy of the matching point, the calibration of the camera, and so on.

To grasp the object successfully, we implement the step-by-step strategy in the experiment. After the robot is moved to the first positioning point, the difference between the positioning point and the goal point is calculated and compensated, the

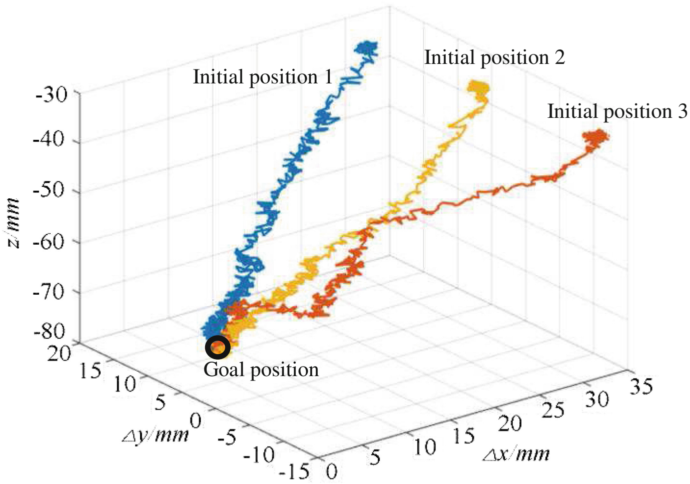


Fig. 9. End-effector positioning based on error compensation

process of object grasping is shown in Fig. 8. The object can be grasped by the end-effector based on the step-by-step object grasping strategy. To check the performance of the position error compensation, we set different position error and make the robot move to the goal position based on compensation, as shown in Fig. 9.

5 Conclusion

In this paper, we analyze and compare four robot kinematic calibration methods for Baxter robot. Due to the characteristic of the Baxter robot, the integration of screw-axis method and kalman filtering perform best in the kinematic calibration. We analyze the monocular-vision and binocular-vision in the object grasping, and propose a step-by-step object grasping strategy. The experiment results show that the proposed method can realize the object grasping for the Baxter robot.

In the future work, the calibration of non-geometrical parameters and the image processing algorithm will be taken into account.

Acknowledgment. This work was partially supported by the Scientific and technological project of Guangzhou (2015090330001), partially supported by the Fundamental Research Funds for the Central University (20152M004), and partially supported by the Natural Science Foundation of Guangdong Province (2015A030310239).

References

1. Smith, C., Karayiannidis, Y., Nalpantidis, L., Gratal, X., Qi, P., Dimarogonas, D.V., Kragic, D.: Dual arm manipulation – a survey. Robot. Auton. Syst. **60**, 1340–1353 (2012)
2. Bloss, R.: Robotics innovations at the 2009 assembly techonology expo. An Int. J. Industr. Robot **37**(5), 427–430 (2010)
3. Oyama, A., Konolige, K., Cousins, S., Chitta, S., Conley, K., Bradski, G.: Come on, our community is wide open for robotics research! In: The 27th Annual Conference of the Robotics Society of Japan, September 2009
4. Baxter robot, Rethink Robotics Company online (2016). http://www.rethinkrobotics.com/. Accessed 15 Mar 2016
5. Elatta, A.Y., Gen, L.P., Zhi, F.L.: An overview of robot calibration. J. Inf. Technol. **3**(1), 74–78 (2004)
6. Denavit, J.: A kinematic notation for lower-pair mechanisms based on matrices. ASME Trans. Appl. Mech. **22**, 215–221 (1955)
7. Park, I., Lee, B., Cho, S., Hong, Y., Kim, J.: Laser-based kinematic calibration of robot manipulator using differential kinematics. IEEE/ASME Trans. Mechatron. **17**(6), 1059–1067 (2012)
8. Zhuang, H., Roth, Z.: A note on singularities of the MCPC model. Robot. Comput. Integr. Manuf. **12**(2), 169–171 (1996)
9. Lou, Y., Chen, T., Wu, Y., Li, Z.: Improved and modified geometric formulation of POE based kinematic calibration of serial robots. In: IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 5261–5266 (2009)

10. Nubiola, A., Bonev, I.: Absolute calibration of an ABB IRB 1600 robot using a laser tracker. Robot. Comput. Integr. Manuf. **29**(1), 236–245 (2013)
11. Nubiola, A., Slamani, M., Joubair, A., Bonev, I.: Comparison of two calibration methods for a small industrial robot based on an optical CMM and a laser tracker. Robotica **32**(3), 447–466 (2014)
12. Renders, J., Rossignol, E., Becquet, M., Hanus, R.: Kinematic calibration and geometrical parameter identification for robots. IEEE Trans. Robot. Autom. **7**(6), 721–732 (1991)
13. Du, G., Zhang, P.: Online serial manipulator calibration based on multisensory process via extended kalman and particle fiters. IEEE Trans. Industr. Electron. **61**(12), 6852–6959 (2014)
14. Chen, C., Huang, H.: Pose estimation for autonomous grasping with a robotic arm system. J. Chin. Inst. Eng. **36**(5), 638–646 (2013)
15. Yang, Y., Cao, Q.: Monocular vision based 6D object localization for service robot's intelligent grasping. Comput. Math. Appl. **64**(5), 1235–1241 (2012)
16. Budiharto, W.: Robust vision-based detection and grasping object for manipulator using SIFT keypoint detector. In: International Conference on Advanced Mechatronics Systems, pp. 448–452 (2014)
17. Hollerbach, J., Giugovaz, L., Buehler, M., Xu, Y.: Screw axis measurement for kinematic calibration of the sarcos dexterous arm. In: IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 1617–1621 (1993)
18. Barker, L.: Vector-algebra approach to extract denavit-hartenberg parameters of assembled robot. NASA Technology Paper, NASA-TP-2191 (1983)
19. Lippiello, V., Siciliano, B., Villani, L.: Position and orientation estimation based on kalman filtering of stereo images. In: IEEE International Conference on Control Applications, pp. 702–707 (2001)
20. Nguyen, H., Zhou, J., Kang, H.: A calibration method for enhancing robot accuracy through integration of an extended kalman filter algorithm and an artificial neural network. Neurocomputing **151**, 996–1005 (2015)
21. Boroujeny, B.: Method of least-squares, Chap. 12. In: Adaptive Filters: Theory and Applications. Wiley, Chichester (2013)