A General Batch-Calibration Framework of Service Robots

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Abstract. Calibration is important to service robot, but the process of calibration is time consuming and laborious. With the popularity of service robot, an automatic and universal calibration system is urgent to be developed, therefore we propose a general batch-calibration framework, Motion Capture System is adopt as an external measurement device in virtual of it can provide realtime, accurate movement data of measured objects. We will show that the system is effective and promising with a case study of odometry calibration.

Keywords: Robot calibration · MoCap system

1 Introduction

Service robots have attracted increasing attention from the commercial companies as well as the research groups in recent years [11]. A service robot is often defined as a robot which autonomously performs daily services for humans, aiming to improve their life quality [17]. Essentially, it is also an artificial electromechanical machine as same as the traditional industrial robot, but expected to be more intelligent, human-interactive, humanoid and safe. Therefore, the tangible service robots have to facing the calibration problem inevitably, which is a common issue with all kinds of robots [2,10,12,28], and it's even more pressing for service robots [13].

The process of tuning the parameters of the kinematic and the dynamic models of a robot is called calibration, this operation is so important that nearly all robots need to be calibrated to perform better after manufacture. Unfortunately, most calibration work is completed by a human operator manually, the process of calibration is time-consuming and laborious. The effects of calibrations usually depend on the experience and knowledge of the operator and devices or tools used. What is worse, to calibrate batch robots which are not coincide with the original design drawing, the same operation is repeated over and over.

As to service robots, an automatic and universal calibration system is much more urgent to be developed for these reasons: (1) A large quantity of service robots will be made to satisfy the demands of families in the future, this market is more huge than industrial robots in long term, it's impossible for manufacturer to

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calibrate every robot manually, a pipeline of automatic calibration is a necessary choice. (2) The cost of the service robots will decrease to a certain amount that is acceptable to most consumer, it means the components of robots may not strictly the same due to their relative low cost, so the calibration is required to mask the difference of hardware. (3) The users of the service robots are ordinary consumers, who are not robotic experts, the calibration should be done before selling to them.

In this paper, we raise the problem of batch calibration of service robots, which needs to be addressed with the coming population explosion of service robots. To solve this problem, we summarize and analyse previous calibration methods, and then propose a general framework of batch calibration, which is especially applicable for service robots. Afterwards, a proof-of-concept of the proposed framework is implemented with an optical Motion Capture System (Mocap) as global measuring tool. Lastly, we conduct the calibration experiments of estimating the odometry parameters of a mobile robot platform as a case study under this framework.

2 Related Work

Robot calibration has a long research history, as Roy et al. said in [23]: "the need for calibration is as old as the field of robotics itself". Many AI planning and learning algorithms [3,4] that can be run on robotic system usually require that the robots have been well calibrated. The mechanical structure of robot systems often slightly change or drift due to wear of parts, reassembling of components, and loosening of joints. The task of calibration is to correct these alterations and keep an accurate model, which describes the relationship between the input control values and actual outputs.

In overviews [15,22], they classified the robot calibration into three levels: The level 1 is simply to ensure the reading from a joint sensor yields the correct joint positions; The level 2 is to extend one joint (in level 1) to multiple joints – i.e., a complex kinematic model; The level 3 considers the dynamic models, deflection of robot links, gear backlash and so on, beyond the kinematics. Each level include four steps: modeling, measurement, identification, and correction.

Large majority of the kinematic calibration studies in literature [9,20,27] are related to the industrial robots, on account of that they are engaged in manufacturing processes which require precise positioning and force control. Follow the same pattern, they employed the Denavit-Hartenberg model or its variants to establish the transformation matrix based on forward kinematics, then determined the unknown parameters with corresponding measurements.

Robot calibration usually involves the collecting of actual measurements, the measurement data are then used to compute the parameters of undetermined models. In general, effective and accurate measurements could greatly improve the precision of the results. The measurements mainly come from two sources: (1) Internal sensors mounted on robots – this method exploits the constrains of measurements from sensors to estimate the model parameters. (2) External measuring equipments – The equipments provide global measurements, usage of these data are straight-forward since the model equations are often included in the models.

A typical case using internal sensors is hand-eye calibration. Here, the cameras are fixed on an end effector or a pan-tilt unit, and vision techniques are applied to acquire the absolute or relative positions of tailor-made signs (e.g., checkerboards) which are easy-recognized. The work [26] solved common formulations of calibration problems using nonlinear optimization with a eye-in-hand systems. Maier et al. [18] also cast a similar hand-eye calibration of Nao's whole-body as a least-squares optimization problem, which is settled with g^2o graph optimization library.

Lots of work focus on the problem how to select optimal measurement configurations for accurate robot calibration, minimizing the variance of the parameters to be estimated. The observability index ([6,16]) was proposed to evaluate the utility of different configuration sets and several criteria were studied out form theoretical points. The recent work [7,18] also designed specific algorithms to get better practical effects. However, our work has not touch on this topic, it's still worth mentioning these work.

Overall, the calibration methods have been extensive researched and have achieved good results in application, but still lack of a general calibration platform which are expected to be automatic and efficient. Our work tries to make a contribution on the exploration and designing of such an calibration prototype under the background – population explosion of service robots. The conception of general calibration platform will be described in next section, in Sect. 3 we introduce our preliminary implement integrating with Mocap system. Lastly, a case study of odometry calibration is presented to show that the system is effective and promising.

3 Conception of the Calibration Platform

3.1 Motivation and Objectives

As mentioned in Sect. 1, the expectable advance of service robots will bring about mass production, but how to raise the efficiency of the indispensable calibration procedure and ensure the quality is still not formally put forward. Currently in practice, this process not only depends on human experience, but also is inefficient and time-consuming (shown in Fig. 1). Our motivation is to establish a platform that could simplify the process, imagine that a new-made robot enter in the platform, just executing a set of benchmark, then individual parameter is set to make every robot in optimal configuration. As shown in Fig. 2, the calibration and quality control is automatically accomplished by the platform without manual intervention.

The design objectives of the platform are:

1. *Automatical*: Our primary aim is to substitute manual operations to increase working efficiency, so the desired platform must be highly automatic, minimizing the need for human intervention to an extreme. Generally, the manual

work almost all concentrate on the measuring, therefore, choosing a automatic measurement tools is crucial for creating such a platform.
2. *Batch-oriented*: The platform is expected to perform calibration in bulk to maintain coordination with quantity production. Robots go through the platform with different process in order just like common product on assembly line.
3. *General*: The platform could apply to different kind of robots with the same way, methods and procedures are roughly changeless, and this principle is reflected in the architecture design of the platform which will describe in the following section.

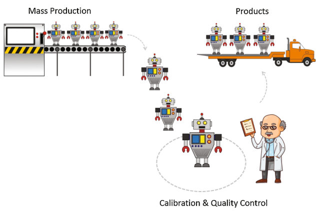

Fig. 1. Traditional robots calibration procedure

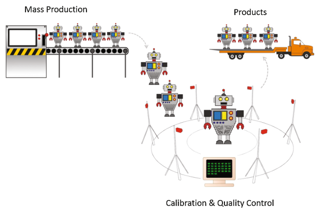

Fig. 2. Calibration in our proposed platform

3.2 Architecture of Calibration Platform

The architecture of our proposed calibration platform is shown in the Fig. 3. The function of this platform is to provide a general way to calibrate all kinds of parameters of robots, and calibration requires measurement data both from robots' internal sensors and external equipments. The internal measurements could be collected from the robot itself by executing certain motion commands. The external measurements are captured by the *Automatic Measuring System* (AMS). Beyond measurement data, a model is necessary to define of a particular calibration, which show clearly what are the unknown parameters and the relationship between observation. Obviously, the models are highly related to specific robots kinematics and calibration cases. In order to improve the generality of this platform, we propose a universal model description language extended from *Unified Robot Description Format* (URDF) [19], which is an *XML* format for representing a robot model. Given the measurements and models, the *General Calibration Solver* is responsible for figuring out the corresponding parameters mostly based on data fitting techniques. Since our purpose is to test the performance of the robots, once the parameters of the models are identified, the calibrated robots will take *Standard Test* and the results are compared with *Performance Criterion*.

Our proposed platform highly generalizes the calibration procedure of service robots, the users could just keep attentions on modeling calibration problem

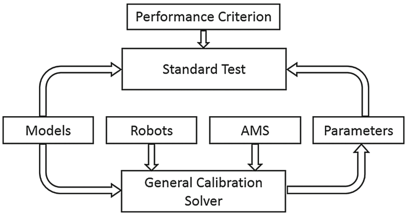

Fig. 3. The concept map of our proposed platform

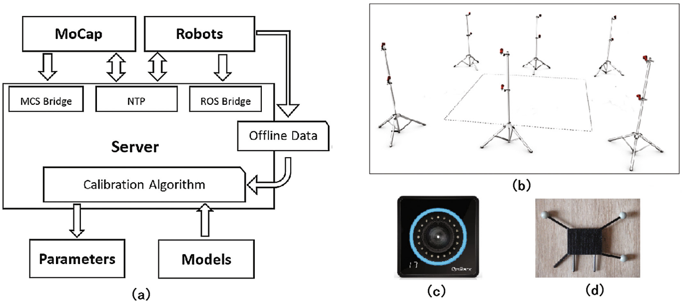

Fig. 4. (a) Modules in our implementation (b) Diagram of Mocap system (c) Optical camera (d) markset

with unified description language and their criterion of performance. Our aim is also to develop a calibration platform, which could perform batch calibration automatically for kinds of robots, meanwhile, it's friendly for users and even a black box.

4 Preliminary Implementation and Case Study

In this section, we firstly present an implementation of the calibration platform proposed above, which employs the *Optical MoCap* as *Automatic Measuring System*. Then, the calibration problems of both odometry and sensor pose are introduced systematically, and the solution is presented by mean of the calibration system.

4.1 Implementation of Calibration System with MoCap

Mocap system is originally used in computer animation for television, cinema, and video games as the technology matured. As shown in Fig. 3, our MoCap system consists of 12 cameras equipped with infrared LED around the camera lens. The reflective markers are attached on the measured objects, the centers of the marker images are matched from the various camera views using triangulation to compute their frame-to-frame positions in 3D space. In order to tract the 6D pose of rigid body in 3D space, usually a markset (at least with 3 marks) is assembled to attach on the measured object. The advantage of introducing such an external measuring equipment is obvious, it provide an automatic and high-accuracy measure method instead of traditional manual measuring, which makes it easy to implement the previous proposed system. As far as we know, this may be the first work to utilize the MoCap into robotic calibration domain though it has already been used in robotics in many tasks [29].

Our system is shown in Fig. 4, the measurements of MoCap and robots are sending to the server realtime through network, the *MCS Bridge* module and *ROS Bridge* on the server are responsible for data receiving and conversing respectively. Since the MoCap, robots and server are stand-alone in different machines, the *NTP* module is used to synchronization time between them. Some large quantities of data (images or point cloud) could be stored in local and then transferred to server off-line.

4.2 Calibration of Odometry Model and Sensor Pose

Calibration of Odometry Model. Odometry is a basic component of mobile robot, which could exploit data from motion sensor (usually encoder or camera) to estimate pose change over time. For many robot application, such as localization and mapping, odometry plays an indispensable role as the input of prior knowledge, hence accuracy odometry could simplify the subsequent process. However, odometry often suffers from kinds of systematic and nonsystematic errors, resulting in a significant decrease in performance [5]. The purpose of odometry calibration is to identify the effective parameters of motion model, which often have small difference between nominal values and therefore cause most of the systematic errors.

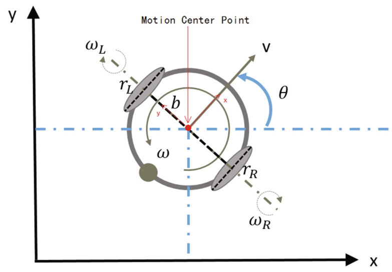

Fig. 5. The structure of differential-driven wheels

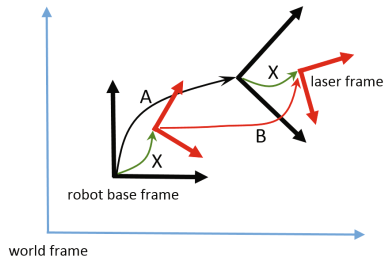

Fig. 6. Illustration of sensor calibration

The odometry motion model in our case is a typical differential wheel structure (shown in Fig. 5). Ignoring the nonsystematic errors in odometry (such as wheel-slippage, uneven floor and etc.), the kinematic model could be represented compactly as following:

$$\begin{bmatrix} v \\ \omega \end{bmatrix} = C * \begin{bmatrix} \omega_R \\ \omega_L \end{bmatrix} \qquad C = \begin{bmatrix} \frac{r_R}{2} & \frac{r_L}{2} \\ \frac{r_R}{b} & \frac{-r_L}{b} \end{bmatrix} \tag{1}$$

In Eq. 1, the v and ω indicate the translational and angular velocity of robot respectively. The $\omega_L(\omega_R)$ and the $r_L(r_R)$ are the rotate speed and radii of left (right) wheel, the b is the distance between two wheels. Once parameter matrix C is determined, the odometry calibration is done.

To collect data under the calibration system, robot are driven to perform movements. Meanwhile, the pose of robot and the encoder data are recorded, thus the relevant parameters would be figured out. Via proper formula manipulation, we could exploit linearity of the parameter matrix C and convert the calibration to a least-squares estimation problem [1] as following:

$$\begin{gathered} \begin{bmatrix} \theta_{N_1,1} - \theta_{0,1} \\ \vdots \\ \theta_{N_p,p} - \theta_{0,p} \end{bmatrix} = \begin{bmatrix} \Phi_{\theta,1} \\ \vdots \\ \Phi_{\theta,p} \end{bmatrix} * \begin{bmatrix} C_{2,1} \\ C_{2,2} \end{bmatrix} \\ \Phi_{\theta,p} = T \left[\sum_{i=0}^{N_p-1} w_{R,i} \sum_{i=0}^{N_p-1} w_{L,i} \right] \end{gathered} \tag{2}$$

In Eq. 2, the $\theta_{0,p}$ and $\theta_{N_p,p}$ are the robot's directions at 0 and N_p moments in the *pth* trajectory sample, the *pth* trajectory contains the encoder data of $0, 1, \cdots, N_p$ moments (totally $N_p + 1$ moments in this trajectory, namely, N_p equal intervals with time T), and $\Phi_{\theta,p}$ is the overall angular change of the *pth* trajectory sample, which is the sum of minor changes in all N_p intervals $\sum_{i=0}^{N_p-1} \Delta\theta_i$. Thus, we can establish a deterministic regressor for this problem by sampling p trajectories. In the same way, we can get the rest of the parameters ($C_{1,1}$ and $C_{1,2}$) in C, which could be further investigated in [1] and not detail here on account of the page limitation.

Thus far, we have elicited the calibration procedure from Eqs. 1 and 2 mathematically, but in practice, the problem is not fully solved since the pose of the motion center on robot could hardly be measured directly. Actually, the motion center point is a virtual point and unobservable. The solution to this issue will be presented in Sect 4.2.

Calibration of Sensor Pose. In our case, our aim is to calibration the plane transformation between the frame of installed laser and the frame of robot base (originated at the motion center point). As shown in Fig. 6, the unknown transformation X in plane has three degree of freedom, thus can be denoted as $X = (l_x, l_y, l_\theta)$. The $A = (A_x, A_y, A_\theta)$ is the related transformation of robot's motion center between two different poses, and the $B = (B_x, B_y, B_\theta)$ is the related transformation of two different laser poses. Hence, we could get an equation by the operation of the homogeneous coordinates transformation [21]:

$$AX = XB \tag{3}$$

In fact, this is the common form of hand-eye calibration problem and has been extensive researched through several approaches ([14,24,25]). Although our problem is a simple case in which the axis of two related transformation is parallel in 2D, previous methods are not fully applicable since they are designed for general cases in 3D. To deduce a solution from Eq. 3 is straightforward:

$$\begin{aligned} \Psi * \begin{bmatrix} l_x \; l_y \; sinl_\theta \; cosl_\theta \end{bmatrix}^T &= \begin{bmatrix} -A_x \\ -A_y \end{bmatrix} \\ \Psi &= \begin{bmatrix} cosA_\theta - 1 & -sinA_\theta & B_y & -B_x \\ sinA_\theta & cosA_\theta - 1 & -B_x & -B_y \end{bmatrix} \end{aligned} \tag{4}$$

Ideally, a consistent system of two solvable homogeneous transform equations of the form $A_1X = XB_1$ and $A_2X = XB_2$ has a unique solution. Considering the existence of noise in measurements, we collect N sets of data and convert the constrain linear problem to an optimization problems:

$$\begin{aligned} min \quad & \varphi^T (\sum_i^N \Psi_i^T * \Psi_i) \varphi \\ s.t. \quad & \varphi_3^2 + \varphi_4^2 = 1 \end{aligned} \tag{5}$$

Find the optimum $\varphi^* = [l_x^*, l_y^*, sinl_\theta^*, cosl_\theta^*]^T$ would solve this problem successfully.

From the view of practical operation, the measurements of B could be acquired by pairwise scan-matching, while the A is actually the movements of robot center point as same as the odometry calibration in previous section. Therefore, how to determine the motion center point and recovery its pose from the MoCap system is an important step.

Determine the Motion Center Point of Robot. Our MoCap system could track the pose of the 3D pose of the rigid body attached on marksets. However, we couldn't put on the markset on the robot's motion center point in practice since it's intangible. So we need a method to acquire the transformation between the base frame and mark-set frame, this is similar to the problem of calibration of sensor pose. Fortunately, a easy method is found to this issue and avoid the interdependence of the two problems. As shown in Fig. 7, the pose of markset in world frame is captured by the MoCap system at any time, based on these information, we could figure out the $X = (h_x, h_y, h_\theta)$ by certain specific movements. Firstly, we command the robot spin on the spot, assuming that the robot's center point is fixed during the operation, thus we could get the radius R and the circle center P_1 of the trajectory. Then we drive the robot forward along the direction of its x axis, meanwhile, the pose of the start and end moment are record as P_2 and P_3.

$$\begin{aligned} \theta_{aux} &= acos(\overrightarrow{P_1P_2} \cdot \overrightarrow{P_2P_3} / \|\overrightarrow{P_1P_2}\| * \|\overrightarrow{P_2P_3}\|) \\ h_x &= R * cos\theta_{aux} \\ h_y &= R * sin\theta_{aux} \\ h_\theta &= Angle(\overrightarrow{P_1P_2}) - Angle(P_2) \end{aligned} \tag{6}$$

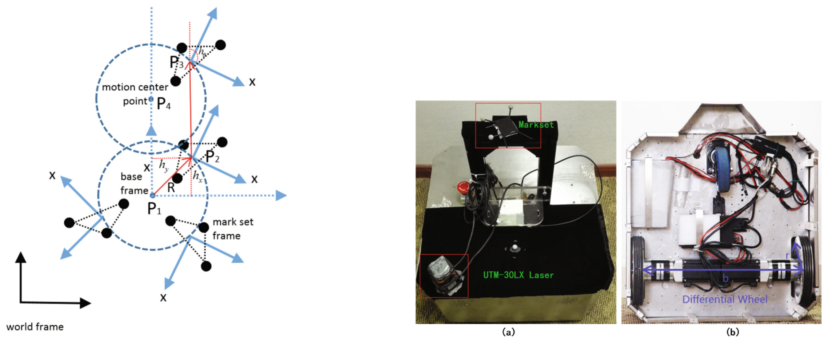

Fig. 7. Illustration of the method to determine the robot's motion center

5 Experiments

In this section, we present our experiments under the proposed calibration system, our aim is to identify the odometry and sensor parameters of the *KeJia* mobile robot.

5.1 Equipment and Environment

The robot used in this experiment is the *KeJia* robot, which has participated in consecutive RoboCup@Home Competitions and once won the world champion. In our experiment, we focus on the basis of the robot since only the wheels and the laser are considered in calibration.

5.2 Configuration and Data Set

We use the following three methods to perform the calibration: (1) Direct measurement of the odometric parameters; (2) The technique described in [8]; (3) The method proposed in this paper.

Method (1) is very straightforward and do not need to collect trajectories. For our robot, the raddi R_L and R_R to are both estimated to be about 96 mm, and the wheelbase is about 420 mm long, we are not able to measure the exact laser pose manually because the center of laser can not be determined manually. For Method (2) and Method (3), We performed three different configurations for the laser pose on the same robot, and collect different trajectories for each configuration, such as straight, circle, S-shape, rotating in place and on only one wheel. For Method (2), we combined the trajectories together and feed them to the method. For our method, we first get the odometry model parameters. For calibration of odometry model parameters trajectories with open path and constant-sign curvature are preferable as detailed in [1], so we cut the closed circles into circle segments to avoid compensation of curvatures. We label the three configurations A, B, and C.

Table 1. Calibration results using [8]

	r_L(mm)	r_R(mm)	b(mm)	l_x(mm)	l_y(mm)	l_θ(deg)
A	97.2	97.3	427.7	81.7	-1.1	-1.9
B	96.6	96.8	422.68	90.06	174.39	-57.3
C	94.56	94.9	414.63	52.15	177.91	38.9

$\alpha = 0.005, N = 8.$

Table 2. Calibration results using our method

	r_L**(mm)**	r_R**(mm)**	b**(mm)**
mean	99.2	97.0	0.4299
std	0.0013	0.0013	0.0014

		l_x**(mm)**	l_y**(mm)**	l_θ**(deg)**
A	**mean**	81.4	2.3	-2.4
	std	0.028	0.017	0.009
B	**mean**	89.8	172.6	-55.7
	std	0.025	0.014	0.012
C	**mean**	53.1	178.3	37.2
	std	0.013	0.007	0.021

5.3 Result and Comparisons

For each of configurations A, B, C, we collect multiple trajectories and divided them into 10 subsets in order to calculate mean and standard deviation.

Obviously, manual measurement cannot reach the precision of millimeters and tenths of degrees. As shown in Tables 1 and 2, the results of method 2 and our method are nearly the same, and it's hard to say which is superior, but our method can separate the calibration problems of odometry and laser pose since we know the ground truth of robot pose from MoCap and the odometry model will be not influenced by laser noise model.

6 Conclusions

In this paper, we claim that a general calibration system is urgent for service robots, to address this problem, the proposed platform highly generalizes the calibration procedure of service robots, and we use odometry calibration as a case study to show that our system is effective and promising.

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