Improving the Positional Accuracy of Industrial Robots by Forward Kinematic Calibration Using Laser Tracker System

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Abstract: Precision positioning of industrial robots is a vital requirement on the factory floor. Robot end effector positioning using joint angle readings from joint encoders and industrial robot forward kinematics (FKs) is a common practice. However, mechanical wear, manufacturing and assembly tolerances, and errors in robot dimension measurement result in parameter uncertainties in the robot FK model. Uncertainties in robot FK result in inaccurate position measurement. In this paper, we use a multi-output least squares support vector regression (MLS-SVR) method to improve the positioning accuracies of industrial robots using a highly accurate laser tracker system, Leica AT960-MR. This equipment is a non-contact metrology one capable of performing measurements with error of less than $3\mu m/m$. To perform this task, industrial robot FK is formulated as a regression problem whose unknown parameters are tuned using laser tracker position data as target values. MLS-SVR algorithm is used to estimate the industrial robot FK parameters. It is observed that using the proposed approach, the accuracy of industrial robot FKs in terms of mean absolute errors of static and near-static motion in all three dimensions decreases from its measured value: from $71.9\mu m$ to $20.9\mu m$ (71% decrease).

1 INTRODUCTION

Industrial robots are vital factory elements to perform various tasks including assembly, object manipulation and object handling (Khanesar & Branson, 2022). Precision positioning is a predominant requirement for industrial robots to maintain their high-quality production and manufacturing. To precisely position industrial robots, accurate forward kinematics (FK) are required to be integrated into control methodologies. Irregularities in industrial robot geometry, robot manufacturing tolerances, tolerances associated with assembly procedure, possible structural deformations, and environmental factors may result in differences between the actual physical parameter values and their nominal counterparts. This discrepancy can lead to uncertainty in industrial robot FK and therefore reduce the overall precision of the robot motion. To overcome the inherent uncertainties in industrial robots FK, calibration approaches are generally used to compensate for differences between nominal and actual parameters (Gao, Li, Liu, & Han, 2021; Nguyen, Zhou, & Kang, 2015).

Industrial robot calibration is usually performed in three levels of joint angle calibration, FK calibration, and non-kinematic calibration (Roth, Mooring, & Ravani, 1987). At calibration level I, joint angle readings from encoder are calibrated using an appropriate relationship between actual joint angle values and encoder angle readings. Robot calibration at level II includes corrections to FK. On level III, non-kinematic calibration includes corrections to robot position due to robot flexibilities. In this paper, calibration is performed at Level II.

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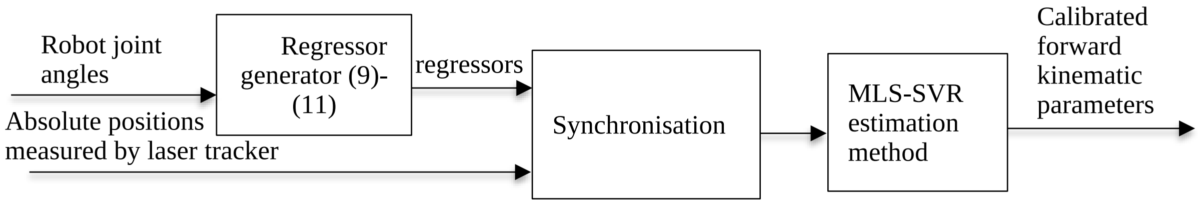

Figure 1 Overall block diagram of the proposed algorithm

Level II calibration, FK calibration, is the process of using real-time data gathered from industrial robots and extra independent measurement equipment to improve positioning precision. The heterogeneous information gathered from multiple measurement systems increases the perception capability of the overall calibration system. To calibrate industrial robots 3D positioning using neural networks, a Leica SMART310 laser tracker is already used to calibrate a PA10 robot arm (Aoyagi, Kohama, Nakata, Hayano, & Suzuki, 2010). Leica AT960 and Leica AT960-MR are used for neural networks position calibration purpose of IRB1410 and a collaborative industrial robot, respectively (Bai et al., 2021; Duong, Trang, & Pham, 2021). A similar approach is used in (Aoyagi et al., 2010; Nguyen et al., 2015) for calibration purpose of Hyundai HH800 robot, a heavy duty industrial robot, using a laser tracker system. To avoid black box robot FK calibration, this paper performs level II calibration of industrial robots by tuning the parameters of its geometrical FK. Therefore, the calibrated industrial robot FK is a traceable one.

To perform level II calibration, this paper proposes the use of multi-output least squares support vector regressions (MLS-SVR), an advanced regression model, to tune industrial robots FKs. This algorithm is a variant of LS-SVR which is a powerful regression algorithm originally introduced by (Vapnik, 1999; Vladimir & Vapnik, 1998). LS-SVR replaces convex quadratic programming problem with convex linear system solving problem. Although the original version of LS-SVR is meant for single output case, its multi-output case has been developed by (Xu, An, Qiao, Zhu, & Li, 2013). Using multi-output LS-SVR (MLS-SVR), it is not required to treat every single output individually. The superior estimation power of MLS-SVR over partial least squares (Abdi, 2003) and kernel partial least squares regression (Rosipal & Trejo, 2001) for benchmark regression problems has already been shown by examples (Xu et al., 2013). Inspired by successful use of MLS-SVR in literature, it is the preferred algorithm in this paper to calibrate industrial robot FK.

In this paper, an MLS-SVR is used to calibrate an industrial robot's FK model. Using a highly accurate laser tracking system, Leica AT960, the absolute 3D positions of an industrial robot are measured. The measurement error of the laser tracking system which is used in this paper is $3\mu m/m$[4]. This equipment is a non-contact metrology one to accurately measure 3D positions. The absolute positions from the laser tracker are then used to estimate industrial robot FK parameters. To do so, first industrial robot FK is formulated as a regression problem. The parameters of industrial robot FK are then estimated using MLS-SVR which is a batch estimation approach. It is observed that using the proposed calibration approach, it is possible to decrease positioning error in terms of mean absolute error (MAE) from its measured value of $71.9\mu m$ to $20.9\mu m$. In other words, using the proposed approach, MAE in all three dimensions decreases by 71%.

This paper is organized as follows: in Section 2, the overall methodology including an industrial robot FK, and the proposed calibration approach are introduced. The experiment setup to perform the measurements is presented in Section 3. Experimental results are presented in Section 4. Section 5 concludes the paper. Acknowledgements and references for this paper are presented in Section 6 and Section 7, respectively.

2 METHODOLOGY

The overall calibration algorithm is presented in this section. Robot joint angle encoders are generally used in industrial robots for positioning purposes. However, uncertainties in robot FK parameters and

[4] https://www.hexagonmi.com/-/media/Hexagon%20MI%20Legacy/m1/metrology/general/brochures/Leica%20AT960%20brochure_en.ashx (visited: 1/5/2022)

geometrical uncertainties impose error on the positional accuracies. To increase the accuracies of FK parameters, MLS-SVR method is used in this paper. Figure 1 demonstrates the overall block diagram of the proposed approach. It is required to formulate industrial robot FK in terms of a regression problem. Synchronisation is required as joint angle measurements and absolute position measurements are conducted using two independent equipment. Joint angle data gathered from industrial robot are at higher frequency of 125Hz. Hence, they are resampled at the laser tracker frequency to obtain synchronisation between the robot and laser tracker. No resampling is conducted on the measurements gathered from laser tracker system to maintain its high accuracy. The data samples occurring at linear robot speed less than *2mm/s* are used for static and near static measurement and calibration. MLS-SVR algorithm is then applied to industrial robot FK using the resulting synchronised data. Details of the overall process are explained in the coming subsections 2.1 and 2.2.

2.1 FK Model of UR5

Industrial robot FK is a function which expresses the Cartesian coordinates of robot within 3D space as a function of robot joint angles. Inverse kinematic is the reverse procedure to assign appropriate joint angles to industrial robots to maintain the desired positions and orientations. The link transformation matrix from the link i-1 to the link i using the Denavit–Hartenberg (D-H) parameters of the robot as in Table 1 depends on the corresponding joint angle of the industrial robot and its D-H parameters (Kufieta, 2014; Sun, Cao, Li, Liang, & Huang, 2017).

$$ {}^{i-1}_{\ \ i}T = \begin{bmatrix} cq_i & -c\alpha_i sq_i & s\alpha_i sq_i & a_i cq_i \\ sq_i & c\alpha_i cq_i & -s\alpha_i cq_i & a_i sq_i \\ 0 & s\alpha_i & c\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1) $$

Table 1 The DH parameters of the 6DOF robot

Link	q	d	a	α
1	q_1	d_1	0	$\pi/2$
2	q_2	0	a_2	0
3	q_3	0	a_3	0
4	q_4	d_4	0	$\pi/2$
5	q_5	d_5	0	$-\pi/2$
6	q_6	d_6	0	0

where $q_i's, i = 1, \dots, 6$ represent the joint angle i, $\alpha_i's, i = 1, \dots, 6$, $a_i's, i = 1, \dots, 6$, *and* $d_i, i = 1, \dots, 6$ present other DH parameters of robot. Furthermore, cq_i, sq_i, $c\alpha_i$, and $s\alpha_i, i = 1, \dots 6$ represent $cos(q_i)$, $sin(q_i)$, $cos\alpha_i$, and $sin(\alpha_i), i = 1, \dots, 6$, respectively. Overall robot transformation matrix in robot base coordinates is obtained as follows.

$$ T_e = {}^0_6T = {}^0_1T\,{}^1_2T\,{}^2_3T\,{}^3_4T\,{}^4_5T\,{}^5_6T \quad (2) $$

The end effector coordinates in all three dimensions are obtained as follows.

$$ \begin{aligned} x_r = {} & d_4 s_1 + a_2 c_1 c_2 + d_6 c_5 s_1 + a_3 c_1 c_2 c_3 \\ & - a_3 c_1 s_2 s_3 + d_5 c_1 c_2 c_3 s_4 + d_5 c_1 c_2 s_3 c_4 \\ & + d_5 c_1 s_2 c_3 c_4 - d_5 c_1 s_2 s_3 s_4 \\ & - d_6 c_1 c_2 c_3 c_4 s_5 + d_6 c_1 c_2 s_3 s_4 s_5 \\ & + d_6 c_1 s_2 c_3 s_4 s_5 + d_6 c_1 s_2 s_3 c_4 s_5 \end{aligned} \quad (3) $$

$$ \begin{aligned} y_r = {} & a_2 s_1 c_2 - d_6 c_1 c_5 - d_4 c_1 + a_3 s_1 c_2 c_3 \\ & - a_3 s_1 s_2 s_3 + d_5 s_1 c_2 c_3 s_4 + d_5 s_1 c_2 s_3 c_4 \\ & + d_5 s_1 s_2 c_3 c_4 - d_5 s_1 s_2 s_3 s_4 \\ & - d_6 s_1 c_2 c_3 c_4 s_5 + d_6 s_1 c_2 s_3 s_4 s_5 \\ & + d_6 s_1 s_2 c_3 s_4 s_5 + d_6 s_1 s_2 s_3 c_4 s_5 \end{aligned} \quad (4) $$

$$ \begin{aligned} z_r = {} & d_1 + a_2 s_2 + a_3 c_2 s_3 + a_3 s_2 c_3 \\ & - d_5 c_2 c_3 c_4 - d_5 c_2 s_3 s_4 + d_5 c_2 s_3 s_4 \\ & + d_5 s_2 c_3 s_4 + d_5 s_2 s_3 c_4 - d_6 c_2 c_3 s_4 s_5 \\ & - d_6 c_2 s_3 c_4 s_5 - d_6 s_2 c_3 c_4 s_5 + d_6 s_2 s_3 s_4 s_5 \end{aligned} \quad (5) $$

Although the values of FK parameters are unknown and will be estimated in this paper, their numerical values according to the robot manufacturer are as follows[5].

$$ \begin{aligned} & d_1 = 0.08916m, a_2 = -0.425m, \\ & a_3 = -0.392m, d_4 = 0.1092m, \quad (6) \\ & d_5 = 0.0947m, d_6 = 0.0823 + d \quad (7) \end{aligned} $$

where d is the distance between the centre of the retroreflector and the centre of the robot end-effector (see Figure 2) which is approximately equal to $0.1695m$. Furthermore,

$$ d_2 = d_3 = 0, \text{ and } a_i = 0, \ i = 1,4,5,6. \quad (8) $$

To conduct the calibration, the direction of the robot is considered on its downward orientation with its TCP axis-rotation vector equal to $(\pi \quad 0 \quad 0)$.

[5] https://www.universal-robots.com/articles/ur/application-installation/dh-parameters-for-calculations-of-kinematics-and-dynamics/ (visited: 1/5/2022)

From (3)-(5), the regressor vectors corresponding to three dimensions: *x*, *y*, and *z* are formulated for MLS-SVR to estimate robot FK parameters.

$$R_x = [s_1c_5, s_1, c_1c_2s_3c_4, c_1c_2c_3c_4s_5, c_1c_2s_3s_4s_5, c_1c_2c_3s_4, c_1c_2c_3, c_1c_2, c_1s_2s_3c_4s_5, c_1s_2c_3c_4, c_1s_2s_3s_4, c_1s_2s_3, c_1s_2c_3s_4s_5, 1], \quad (9)$$

$$R_y = [c_1c_5, c_1, s_1c_2s_3c_4, s_1c_2c_3c_4s_5, s_1c_2s_3s_4s_5, s_1c_2c_3s_4, s_1c_2c_3, s_1c_2, s_1s_2s_3c_4s_5, s_1s_2c_3c_4, s_1s_2s_3s_4, s_1s_2s_3, s_1s_2c_3s_4s_5, 1] \quad (10)$$

and

$$R_z = [s_2s_3s_4s_5, s_2s_3c_4, s_2c_3c_4s_5, s_2c_3s_4, s_2c_3, s_2, c_2s_3c_4s_5, c_2s_3s_4c_2s_3, c_2c_3s_4s_5, c_2c_3c_4, 1] \quad (11)$$

These regressor values are used in the next subsection to tune the FK parameters

2.2 Multi-output least squares support vector regression

Let the multioutput regression problem to be solved be:

$$\Upsilon = \Phi^T \Pi \quad (12)$$

where $\Upsilon = [X \quad Y \quad Z] \in \mathbb{R}^{N\times3}$, and $X, Y,$ and Z are the position measurements in all three dimensions using the laser tracker system. The regressor matrix Φ is defined as follows.

$$\Phi = \begin{bmatrix} R_x^1 & R_y^1 & R_z^1 \\ & \vdots & \\ R_x^N & R_y^N & R_z^N \end{bmatrix}^T \quad (13)$$

where $\Phi \in \mathbb{R}^{N\times40}$ is the regressor matrix and $\Pi = [\Pi_1 \quad \Pi_2 \quad \Pi_3] \in \mathbb{R}^{40\times3}$ is the vector of unknown parameters of industrial robot FK in laser tracker coordinates. R_x^i, R_y^i, and R_z^i represent the *i*-th regressor vector sample. Xu *et al.* recently proposed MLS-SVR for solving the multioutput regression problems. The objective function to be minimized in this case is as follows (Xu et al., 2013).

$$\min_{\pi_0\in\mathbb{R}^{40}, V\in\mathbb{R}^{40\times3}} \mathcal{J}(\pi_0, V, \Xi) = \frac{1}{2}\mathrm{trace}(\pi_0^T\pi_0) + \frac{\lambda}{2m}\mathrm{trace}(V^TV) + \frac{\gamma}{2}trace(\Xi^T\Xi),$$
$$s.t. \Upsilon = \Phi^T\rho + \Xi \quad (14)$$

where the matrix $\Xi = [\xi_1 \quad \xi_2 \quad \xi_3] \in \mathbb{R}_+^{N\times3}$ is a matrix consisting of slack variables, $\Pi = (\pi_0 + v_1, \pi_0 + v_2, \pi_0 + v_3) \in \mathbb{R}^{40\times3}$ and $\gamma \in \mathbb{R}^+$ is a positive real regularized parameter. The Lagrangian function to solve the problem of (13) is

$$\mathcal{L}(\pi_0, V, \Xi, \mathrm{A}) = \mathcal{J}(\pi_0, V, \Xi) - trace(A^T(\Phi^T\rho) + \Xi - \Upsilon) \quad (15)$$

where $A = (\alpha_1, \alpha_2, \alpha_3) \in \mathbb{R}^{N\times3}$, include all Lagrange multipliers, $\alpha_i \in \mathbb{R}^{N\times1}, i = 1,2,3$. Using the Karush-Kuhn-Tucker conditions for optimality and a set of algebraic modifications leads to an equivalent optimisation problem which does not include π_0 parameters.

$$\min_{V\in\mathbb{R}^{40\times3}} \mathcal{J}(V, \Xi) = \frac{\lambda^2}{54}V1_31_3^TV^T + \frac{\lambda}{6}trace(V^TV) + \frac{\gamma}{2}trace(\Xi^T\Xi),$$
$$s.t. \Upsilon = \Phi^T\rho + repmat\left(\frac{\lambda}{3}\Phi^TV1_3, 1,3\right) + \Xi \quad (16)$$

where $1_3 = [1 \quad 1 \quad 1]^T$. The solution to the optimisation problem of (16) is available using the method presented in (Xu et al., 2013). The method to solve the optimisation problem of (16) is summarised in the following six main steps.

1. solve η, and ν from $H\nu = P$, and $H\nu = \Upsilon$ where $P = blockdiag(1_N, 1_N, \ldots, 1_N) \in \mathbb{R}^{3N\times3}$, and $H = \Omega + \gamma^{-1}I_{3N} + (3/\lambda)Q \in \mathbb{R}^{3N\times3N}$, $Q = blockdiag(K, K, K) \in \mathbb{R}^{3N\times3N}$, $K = \Phi^T\Phi \in \mathbb{R}^{N\times N}$
2. Compute $S = P^T\eta$

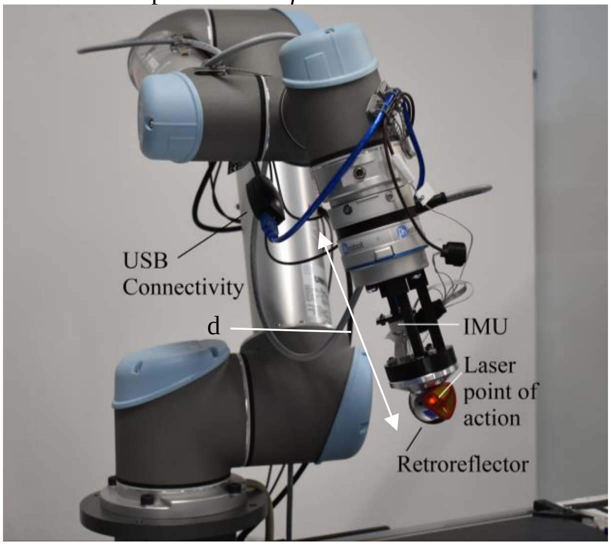

Figure 2 UR5 with retroreflector mounted on it as the target for laser tracker

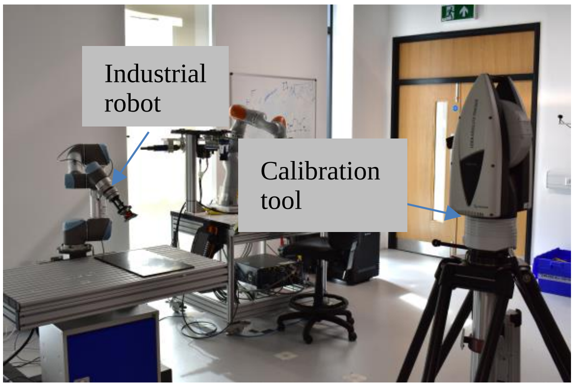

Figure 3 Overall calibration system: UR5 industrial robot and Leica laser tracker system

3. Find b and α as $b = S^{-1}\eta^T\Upsilon$, $\alpha = \nu - \eta b$
4. Find V from $V = \frac{3}{\lambda}\Phi\mathrm{A}$
5. Find π_0 from $\pi_0 = \sum_{i=1}^{3} \Phi\alpha_i$
6. Find Π from $\Pi = (\pi_0 + v_1, \pi_0 + v_2, \pi_0 + v_3)$

3 EXPERIMENT SETUP

3.1 Hardware Setup

The hardware used to perform this experiment is composed of an industrial robot and a calibration equipment (see Figure 3). In this subsection, detailed explanations of the equipment are presented.

3.2.1 Calibration Equipment

To conduct the calibration test, the 3D real time position of a retroreflector mounted on the UR5 end effector is measured using a laser tracker. The laser tracker used in this experiment is AT960-MR from Hexagon metrology GMBH, Wetzlar. It is a widely used measurement device in industry to inspect critical distances, locations and surfaces (Kyle, 1999) (see Figure 4). The target used in these experiments is a precision Leica 1.5" red ring reflector which is detectable through the laser tracker at the maximum distance of *60 m @10Hz* with the accuracy of $3\mu m/m$. The reflector used in this experiment is using the principle of corner cube. To reflect the beam, three plane mirrors at right angles to one another are used. The measurement point is the centre of the reflector. Further specifications and environmental conditions of the laser tracker are presented in Table 2.

3.2.2 Industrial robot

The industrial robot used in these experiments is a Universal Robots, UR5 capable of handling 5Kg load with angular velocity of $180°/sec$. Real time industrial robot joint angles are measured using on-board joint angle encoders. To collect this data, wired network connectivity is used to connect the main robot controller to a PC. The software used for connectivity is ROS Melodic operating under Linux 18.04 operating system. The ROS driver used for UR5 is the one available through a GitHub webpage[6]. This ROS driver publishes some *rostopics* which contain joint angle data including joint angle values, angular velocities, and motor currents. The sample time for the data transfer from robot to PC slightly varies but its mean value is equal to $8msec$. Overall, 38 waypoints are programmed for the robot, and it travels them linearly in *600 sec*. It is required to resample position data from the robot to match laser tracker frequency (10Hz).

3.2.3 Data Gathering and Pre-processing

To gather data points to perform static calibration, as it is required for a level II robot calibration, the absolute position data are gathered from the robot using the laser tracker system. The laser tracker is connected to the PC using a Wi-Fi connectivity. The software used for data gathering is Spatial Analyzer software (see Figure 5), and the sample time for this device is set to *100 msec*. For measurements in Spatial Analyzer software, it is required to assign the three axes and the origin. To do so, two linear motions are performed using the robot along x-axis and y-axis. The zero coordinate for the laser tracker and its three axes are assigned within Spatial Analyzer software. The total number of points gathered using the laser tracker is equal to 6000. Moreover, since robot and laser tracker use different timing, it is required to synchronise them *i.e.*, to shift them so that they match each other timewise. Finally, for performing static and near static calibration, the points at which the linear speed of the robot are less than *2mm/sec* are extracted. Total number of these points are *209* points.

4 EXPERIMENTAL RESULTS

4.1 Results

The results of the calibration process proposed in this paper are presented in Figures 6- 8. These figures

6 https://github.com/UniversalRobots/Universal_Robots_ROS_Driver

Table 2 Measuring equipment characteristics and specifications

Environmental working conditions	IP54**:** The IEC-certified sealed unit guarantees ingress protection against dust and other contaminants.
Operating temperature	Wide operating temperature range of -15 to 45 degrees Celsius
Temperature compensation	MeteoStation: Integrated environmental unit monitors conditions including temperature, pressure, and humidity to compensate for changes
ISO certification	ISO 17025
Connectivity	Wifi and LAN
Detector features	Red ring reflector - 1.5” radius: 19.05 mm ±0.0025 mm, centring of optics: < ±0.003 mm, ball roundness: ≤0.003 mm, acceptance angle: ±30°, weight:170gr
Data output rate	Measurement rate of up to 1000 points per second
Distance accuracy	40 metres in diameter and a 6DoF measuring volume of up to 20 metres
Laser safety	Laser class 2

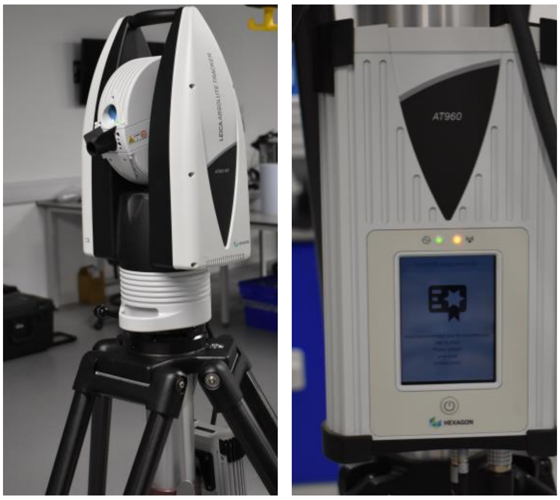

Figure 4 Laser tracker system (a) Camera and tracking system (b) Controller unit

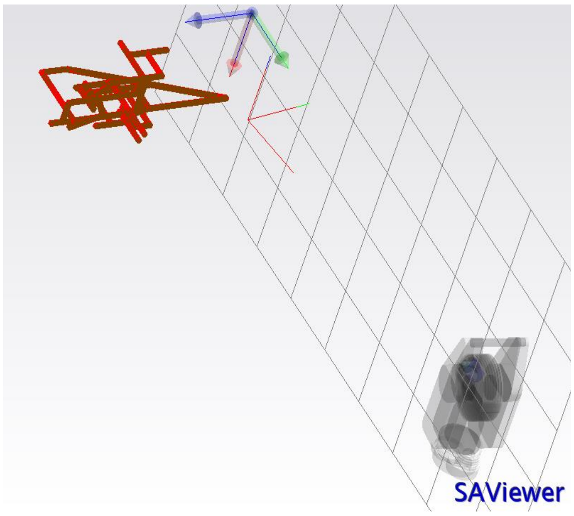

Figure 5 Points measured by laser tracker system in Spatial Analyzer software

show that the positions obtained through the calibrated UR5 FK are much closer to its real 3D positions measured by laser tracker. The numerical values presented in Table 3 demonstrate the improvement made using the proposed calibration method. In all three positional dimensions, the MAE associated with the calibrated FK of UR5 is less than its uncalibrated value. It is further observed that the mean MAE of all three dimensions is reduced from 71.9μm for uncalibrated FK to 20.9μm for the calibrated FK using the proposed calibration method, which is 71% improvement in the measurement.

The trend of error associated with original FK of industrial robots and its calibrated version are presented in Figures 9- 11, respectively. It is observed from these figures, that errors corresponding to the calibrated FK are much less than the ones associated with uncalibrated FK.

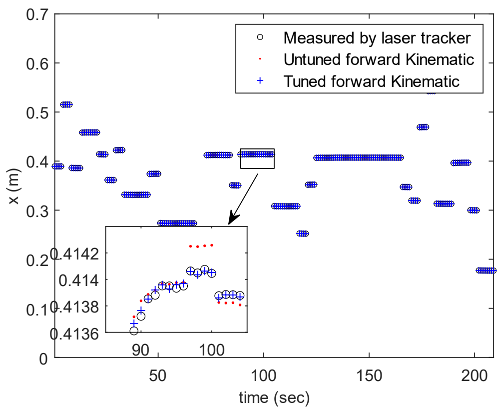

Figure 6 Robot movements in 3D coordinates, x-axis

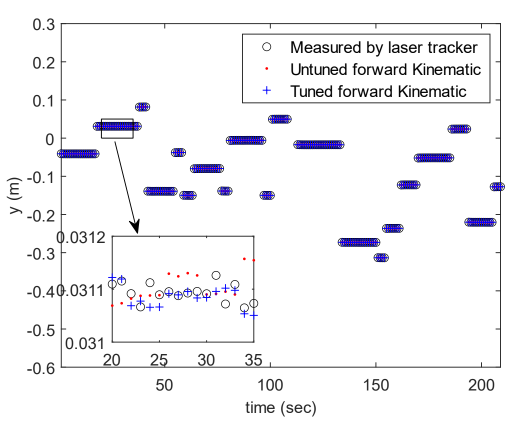

Figure 7 Robot movements in 3D coordinates, y-axis

Table 3 FK error indexes

Performance indexes		*Calibrated*	*Uncalibrated*
MAE	X	$24.4\mu m$	$94.6\mu m$
	Y	$21.7\mu m$	$67.9\mu m$
	Z	$16.5\mu m$	$53.3\mu m$
	Mean	$20.9\mu m$	$71.9\mu m$
σ_i	X	$32.0\mu m$	$124.2\mu m$
	Y	$28.6\mu m$	$99.1\mu m$
	Z	$23.7\mu m$	$67.6\mu m$
	Mean	$28.3\mu m$	$99.8\mu m$

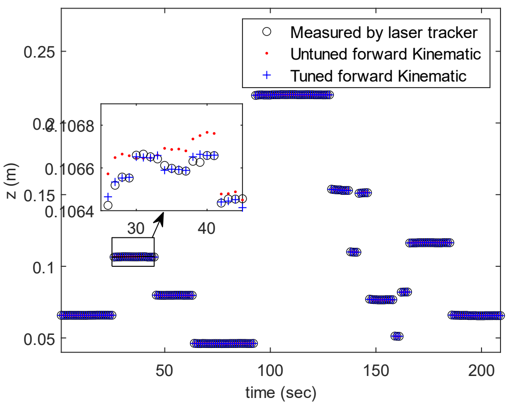

Figure 8 Robot movements in 3D coordinates, z-axis

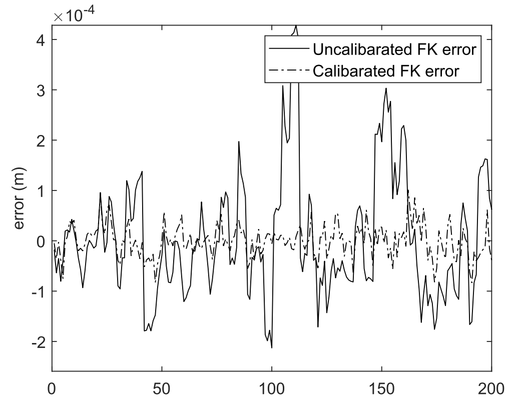

Figure 9 Position error in x-axis

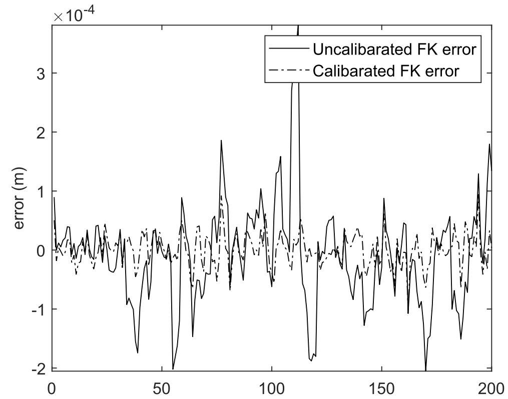

Figure 10 Position error in y-axis

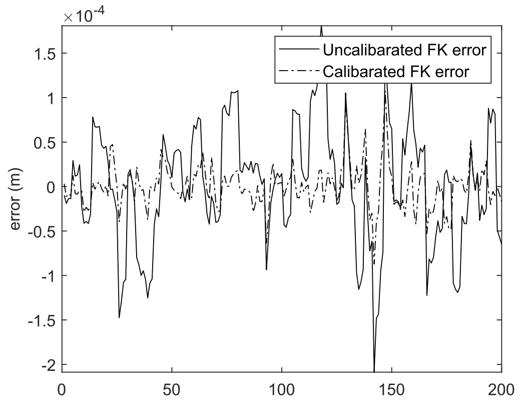

Figure 11 Position error in z-axis

5 CONCLUSIONS AND FUTURE RESEARCH

The uncertainties associated with FK of industrial robots are mainly due to manufacturing and assembly tolerances, dimension measurement uncertainties, and wears and tears of robot. FK uncertainties result in positioning error. This paper presents an FK calibration method for industrial robot using laser

tracker measurement system. Robot joint angles are measured using on board joint encoders. Robot joint angles are collected and transferred to PC using ROS-Melodic software. Static and near static measurements are performed on the robot. The industrial robot FK is formulated as a multi-output regression problem. The industrial robot coordinates measured by a laser tracker system (Leica AT960) is then used in an MLS-SVR algorithm to calibrate FK. The industrial robot used in the calibration experiment is an UR5, an industrial robot manufactured by Universal Robots. It is observed that using the proposed calibration approach, it is possible to decrease the position errors in terms of mean absolute errors from its measured value of $71.9\mu m$ to $20.9\mu m$ which is 71% improvement.
As a future study, data fusion between data gathered from inertia measurement unit and gyroscopic measurements will be considered to improve the accuracy of positional measurements.

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