Accuracy improvement studies for Remote Maintenance Manipulators

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Accuracy improvement studies for remote maintenance manipulators

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1. Introduction

The remote handling of big size and massive component in a challenging environment plays a crucial role in the construction of future fusion reactors. For the EU DEMO blanket remote handling systems (see Figure 1), the required positioning tolerance is expected to be in the tens of millimeters. However, due to big size and massive weight of the manipulator and its lifting component, the unknown errors originated from geometric dimensions, dynamic motion, as well as joint and link deformations will become considerably large, in the worst case it would be up to several hundred millimeters. To satisfy the accuracy requirement, both geometric and dynamic errors should be calibrated and then compensated in controller.

Dynamic calibration involves experimental identification of dynamic parameters such as link masses, joint friction, and the moment inertia. In general, an inverse dynamic model has to be established, and then the dynamic parameters are grouped as base parameters according to the rules defined by Khalil et al [6]. In order to identify the base parameters, optimal excitation trajectories are indispensable. In the literature, periodic excitation trajectories based on Fourier series are the most commonly used ones[7]. In this paper, a symbolic linear dynamic identification model was built up. Fourier series excitation trajectories are generated by minimizing condition number of the observation matrix, and then SimMechanics was used to simulate the real robot to get joint torques for dynamic parameter identification purpose. A global optimization method, i.e. Differential Evolution (DE) algorithm[8], is utilized in three different objective functions in order to identify geometrical errors, dynamic errors, and generate Fourier series excitation trajectories respectively.

2. Kinematic modeling and identification

2.1 The principle of the proposed method

The idea behind this method is to calculate the volume of a parallelepiped (Vₚ) defined by three vectors given four points: A(x₁, y₁, z₁), B(x₂, y₂, z₂), C(x₃, y₃, z₃), D(x₄, y₄, z₄), as shown in figure 2. The volume of the

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tetrahedron \((V_i)\) can be obtained by calculating the scalar triple product of the three vectors as seen in equation (1).

![Diagram](image)

Fig. 2. Principal of the proposed method.

\[
V_p = \Delta \bar{D} \cdot (\Delta \bar{B} \times \Delta \bar{C}), \quad \dot{V}_i = \frac{1}{6} V_p
\]  

(1)

2.2 Kinematic identification model

The forward kinematics of a serial manipulator can be obtained using the commonly used Denavit-Hartenberg conventions [6].

\[
bT_E = \prod_{i=1}^{n} b_i A_i \quad bT_E = \prod_{i=1}^{n} b_i A_i
\]

(2)

\[
i^{-1} A_i = \begin{bmatrix}
    c\theta_i & -s\theta_i & 0 & d_i \\
    s\alpha_i \cdot s\theta_i & c\alpha_i \cdot c\theta_i & -s\alpha_i \cdot r_i & s\alpha_i \\
    -s\alpha_i \cdot s\theta_i & c\alpha_i \cdot c\theta_i & s\alpha_i \cdot r_i & c\alpha_i \\
    0 & 0 & 0 & 1
\end{bmatrix}
\]

(3)

\[
i^{-1} A_i = \begin{bmatrix}
    c\theta_i & -s\theta_i & 0 & d_i' \\
    c\alpha_i \cdot s\theta_i & c\alpha_i \cdot c\theta_i & -s\alpha_i \cdot r_i' & s\alpha_i' \\
    -s\alpha_i \cdot s\theta_i & c\alpha_i \cdot c\theta_i & s\alpha_i \cdot r_i' & c\alpha_i' \\
    0 & 0 & 0 & 1
\end{bmatrix}
\]

(4)

where \(bT_E\) and \(bT_E\) denote the nominal and the predicted position and orientation of the endpoint frame \(\{E\}\) with respect to the robot base frame \(\{B\}\); \(i^{-1} A_i\) denotes the homogeneous transformation matrix between two successive joints; \(s\alpha_i\) represents \(\sin(\alpha_i + \delta\alpha_i)\), and \(\alpha_i\) represents a small unknown parameter errors, the same rules are also applied to the other two geometric parameters \(d_i\) and \(r_i\).

For this method, the only thing need to know is the joint sensor readings and the distance between the end-effector and a smooth planar surface. By using these measured data, a predicted point on the planar surface can be calculated according to equations (2) and (4). Repeating this process for different robot configurations on and different plane locations, an identification cost function can be established as seen in equation (5). And a global optimization algorithm, Differential Evolution algorithm, was employed to identify the unknown parameters.

\[
\min_{\alpha, \delta\alpha, \delta r, \delta d} \sum_{i,j} \sum_{k=1}^{n} \text{abs}(V_i^j - V_i^j_k),
\]

(5)

where \(V_i^j\) is the predicted tetrahedron volume including unknown variables \(\delta\alpha, \delta\delta\) and \(\delta r\) for the \(i\)-th plane and \(j\)-th.

It should be noted that the plane can be fixed in any location of the robot workspace, and the robot can be calibrated without calibrating the transformation from plane coordinate system with respect to robot base coordinate system. This makes robot calibration very easy and convenient to implement on the site.

3. Dynamic modeling and identification

3.1 Dynamic identification model

This paper employs inverse dynamic model and least squares estimation method to estimate dynamic parameters. The dynamic model can be derived using the Euler-Lagrange formulation [6] and written as:

\[
\tau = M(q)\ddot{q} + B\dot{q} + Cq^2 + Q + \tau_f
\]

(6)

where \(M\) is inertial matrix, \(B\) matrix containing the elements of Coriolis forces, \(C\) matrix containing the elements of centrifugal forces, \(Q=[Q_1 \ldots Q_6]^T\) is gravity forces vector,

\[
\ddot{q} = \begin{bmatrix}
    \ddot{q}_1 \\
    \ddot{q}_2 \\
    \ddot{q}_3 \\
    \ddot{q}_4 \\
    \ddot{q}_5 \\
    \ddot{q}_6
\end{bmatrix}
\]

(7)

\[
\dot{q}_i = \begin{bmatrix}
    \dot{q}_i \\
    \dot{q}_i ^2
\end{bmatrix}, \quad \tau_f = f_\tau \dot{\phi} + f_s \text{sgn}(\dot{\phi})
\]

(8)

A linearly parametrized form of equation (6) is:

\[
\tau = \mathbf{Y}(q, \dot{q}, \ddot{q}) \mathbf{Z}_\tau
\]

(9)

where \(\mathbf{Y}(q, \dot{q}, \ddot{q}) \in \mathbb{R}^{m \times n}\) is observation matrix, \(\mathbf{Z}_\tau \in \mathbb{R}^{n \	imes 1}\) is a vector of 13 standard parameters including six components of the inertia matrix (\(XX, XY, ZX, YY, YZ, ZZ\)), three components of the first moments (\(MX, MY, MZ\)), the mass (\(M_0\) of link \(j\), the rotor and gears moment (\(I_{a0}\)), and viscous and Coulomb friction coefficients (\(f_v, f_v\)). For a rigid robots with \(n\) joints, the number of standard parameters can also be further reduced by eliminating dependent parameters or regrouping with others, finally a dynamic equation with minimal identifiable parameters can be obtained as:

\[
\tau = \mathbf{Y}(q, \dot{q}, \ddot{q}) \mathbf{Z}_\tau
\]

(10)

where \(\mathbf{Y}(q, \dot{q}, \ddot{q}) \in \mathbb{R}^{m \times n}\) is a subset of the independent columns of \(\mathbf{Y}\) and \(\mathbf{Z}_\tau \in \mathbb{R}^{n \times 1}\) are the base parameters [9].

3.2 Trajectory parametrization and optimization

To identify the base dynamic parameters, an excitation reference trajectory must be generated to persistently excite a given system. In this work, a periodic Fourier series trajectory was employed. The trajectory of each joint can be expressed as a sum of \(N\) harmonic sines and cosines functions [10]. The \(i\)-th joint position, velocity, and acceleration can be written as:

\[
q_i(t) = \sum_{j=1}^{N} \frac{a_j}{\omega_j l} \sin(\omega_j l t) - \frac{b_j}{\omega_j l} \cos(\omega_j l t)
\]

(11)

\[
\dot{q}_i(t) = \sum_{j=1}^{N} a_j \cos(\omega_j l t) + b_j \sin(\omega_j l t)
\]

(12)

\[
\ddot{q}_i(t) = \omega_j \sum_{j=1}^{N} b_j l \cos(\omega_j l t) - a_j l \sin(\omega_j l t)
\]

(13)
Assuming the positions, velocities, accelerations and motor torques are measured at a sampling frequency $\omega_s$ and the fundamental frequency of the trajectories is $\omega_f$, then a number of $M = \omega_f / \omega_s$ samples can be recorded, and an over-determined equations can be written as:

$$A \chi_b = b,$$

where:

$$A = \begin{bmatrix} Y(q_1, \dot{q}_1, \ddot{q}_1) \\ \vdots \\ Y(q_M, \dot{q}_M, \ddot{q}_M) \end{bmatrix}, \quad b = \begin{bmatrix} \tau_1 \\ \vdots \\ \tau_M \end{bmatrix}$$

The excitation trajectory can be optimized by minimizing the condition number of the observation matrix $A$. The global optimization algorithm DE can be used for this purpose. The trajectory is defined to have zero initial joint positions, velocities and accelerations. And the maximal joint positions, velocities and accelerations are denoted as $q_{\max}$, $\dot{q}_{\max}$, and $\ddot{q}_{\max}$ respectively as seen in the following equations:

$$\min_{\chi_b} = \text{cond}(A)$$

subject to

$$\sum_{i=1}^{N} b_i a_{i1} = 0, \quad \sum_{i=1}^{N} a_i = 0, \quad \sum_{i=1}^{N} \omega_i b_i = 0$$

$$\sum_{i=1}^{N} \frac{1}{\omega_i} \sqrt{a_i^2 + b_i^2} \leq q_{\max}$$

$$\sum_{i=1}^{N} \sqrt{a_i^2 + b_i^2} \leq \dot{q}_{\max}$$

$$\omega_f \sum_{i=1}^{N} \sqrt{a_i^2 + b_i^2} \leq \ddot{q}_{\max}$$

After the joint positions, velocities, accelerations and torques are obtained, the base dynamic parameters can be obtained by minimizing a least squares objective function using DE global optimization algorithm.

$$\min_{\chi_b} \| A \chi_b - b \|^2$$

where $b$ represent the measured torques, and $A \chi_b$ represent the predicted torques with unknown variables.

4. Simulation and experimental results

To verify the effectiveness of the proposed kinematic and dynamic calibration methods, a six-DOF Mitsubishi RV-3SB manipulator was used. The modified DH parameters are listed in table 1. $\theta_j$ to $\theta_6$ are joint variables whose values are recorded according to joint sensor reading. $r_7$ is the measured distance from robot end-effector to the tip point on the plane surface, which can be obtained by a high accuracy (at least $\mu m$ level) range finder or dial indicator. The plane surface has to be put at more than four different locations within the workspace. The plane surface should be very smooth and the flatness should be up to several micrometers. Totally there are 17 parameters can be identified. Most of parameters on the base frame and endpoint frame cannot be identified.

<table>
<thead>
<tr>
<th>Link</th>
<th>$a_i$</th>
<th>$d_i$ (mm)</th>
<th>$\theta_i$</th>
<th>$r_i$ (mm)</th>
<th>$\beta_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>base</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>$\theta_1$</td>
<td>0</td>
<td>$r_1=350$</td>
</tr>
<tr>
<td>2</td>
<td>$-\pi/2 + \delta d_2$</td>
<td>$d_2 + \delta d_2$</td>
<td>$\theta_2$</td>
<td>$r_2 + \delta r_2$</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>$0 + \delta d_3$</td>
<td>$d_3 + \delta d_3$</td>
<td>0</td>
<td>$r_3 + \delta r_3$</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>$-\pi/2 + \delta d_4$</td>
<td>$d_4 + \delta d_4$</td>
<td>$\theta_4$</td>
<td>$r_4 + \delta r_4$</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>$\pi/2 + \delta d_5$</td>
<td>$0 + \delta d_5$</td>
<td>$\theta_5$</td>
<td>$r_5 + \delta r_5$</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>$-\pi/2 + \delta d_6$</td>
<td>$0 + \delta d_6$</td>
<td>$\theta_6$</td>
<td>$0 + \delta r_6$</td>
<td>0</td>
</tr>
<tr>
<td>Tip</td>
<td>$0 + \delta r_7$</td>
<td>$0 + \delta d_7$</td>
<td>0</td>
<td>$85 + r_7$</td>
<td>0</td>
</tr>
</tbody>
</table>

Experimental tests are conducted by using a vision-based calibration system to measure the distance $r_7$ and to record the sensor readings of each joint. Figure 3 shows that the position error of the end-effector is about 1.6 mm before calibration, after calibration, the position error has been reduced to 0.3 mm.

![Fig. 3. Experimental calibration results.](image)

To effectively identify the dynamic model parameters, the information of a certain combinations of positions, velocities and accelerations is indispensable. In this work, a Fourier series with five harmonic sine and cosine functions is selected to generate excitation trajectories of positions, velocities and accelerations. By using DE optimization algorithm to the equations (16) and (17), the coefficients of Fourier series can be found and then the optimal joint position trajectories can be obtained as seen in figure 4.

![Fig. 4. Joint position excitation trajectories.](image)
joint torques. By selecting sampling frequency $\omega_s$ as 150 Hz and fundamental frequency $\omega_f$ as 0.1 Hz, a total number of 1500 samples per period can be obtained. Substituting these samples into equation (18) for optimization, then the base dynamic parameters can be identified. Figure 6 shows the Cartesian position of the end-effector during the Fourier series trajectory. And figure 7 shows the difference between the estimated torques using identified parameters and the measured torques using SimMechanics. It can be seen the trajectory matches very well with only a little deviations.

Substituting these samples into equation (18) for optimization, then the base dynamic parameters can be identified. The advantage of this method is that the plane surface can be put in any unknown locations of the manipulator workspace without base calibration in advance. The only thing need to know is to record each joint sensor readings and measure the distance between the robot end-effector and the plane endpoint. This feature makes on-site calibration easy and convenient to implement. This paper has also investigated a SimMechanics simulation based dynamic calibration method. For the remote handling of big size and massive weight component, SimMechanics together with Simulink package in Matlab environment provides an alternative way to verify the effectiveness of dynamic calibration method and its control strategy. The future work will focus on the experimental validation of the proposed dynamic calibration method.

Acknowledgments

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