Proceeding of the IEEE
International Conference on Robotics and Biomimetics
Dali, China, December 2019

Dynamic Parameter Identification of a 6-DOF Industrial Manipulator Considering Friction Model

Xiaojun Ding, Jin Hou, Haoyuan Yi, Bin Han, *Member, IEEE,* Xin Luo*,*Member, IEEE*

State Key Laboratory of Digital Manufacturing Equipment and Technology,
Huazhong University of Science and Technology, Wuhan 430074, China

Abstract* - Dynamic parameters identification is essential for motion control of industrial robots. Precise identification is still an open issue due to friction, transmission backlash, and measurement noises of sensors. In this paper, based on a minimum set of parameters considering friction model, a unified identification approach is proposed. With this method, some essential data from robot's joints motion can be sampled and calculated at the same time, thus all dynamic parameters are also acquired at one time. The 5-th order Fourier series is used as the excitation trajectory. The optimal excitation trajectory is determined by minimizing the condition number, and the minimum set of parameters of the robot is obtained by combining with the least square method. Experiment results taken on a 6-DOF industrial manipulator Staubli TX-60 verified the correctness of the presented method.

Index Terms - Dynamic Parameters, Identification algorithm, industrial robotic manipulator, Trajectory optimization

I. Introduction

Precise parameters of a dynamic model are very important for design of advanced model-based controller, verification of simulation results as well as path planning. Especially in industrial robot technology, model-based control is essential to improve the accuracy and reliability of the system [1]-[2]. The complexity of the robot structure makes it impossible to measure these parameters directly, the inertial parameters obtained from CAD software are difficult to meet the required precision due to its failure to model each part of the robot accurately. Therefore, the experiment based robot parameter identification is the only effective method to obtain accurate dynamic parameters [3]-[4].

Generally, dynamic parameters identification mainly includes parameter estimation method and identification strategy. At present, the mainstream dynamic parameters identification methods were based on a linearization dynamic model, i.e., the dynamic characteristics of a robot can be regarded as a linearization function of its inertial parameters. For parameters estimation, the least square method [3], weighted least square method [5], Kalman filter method [5] and maximum likelihood method [6]-[7] have more commonly been used. Although the least square method simplifies calculation, it is sensitive to measurement noise and requires high data processing. The weighted least square method solves the noise sensitive problem to some extent. Kalman filter solves the problem of sampling noise from the system modelling, but it is very sensitive to initial state and its convergence at slow speed. The maximum likelihood method solves the measurement noise problem from a statistical framework. The algorithm is relatively complex and can be simplified to a weighted least squares when torque noise is only considered. Moreover, with the development of intelligent techniques, many scholars used artificial intelligence algorithm to solve the problem of parameter estimation [8]. Practice showed that, on the one hand, using neural network to identify dynamic parameters can improve identification efficiency and accuracy by its strong virtue of generalization ability, fault tolerance and good convergence. On the other hand, online identification can be realized, and real-time parameters can be obtained according to real-time data samples. However, the structure and parameters of the constructed neural network cannot reflect the actual physical meaning of the robot system. The system it represents is still a "gray box" system. When there are many dynamic parameters to be identified, it is difficult to determine the appropriate network structure.

For the identification strategy, most of aforementioned identification methods adopt the "unified identification" and "one by one identification". For "one by one identification", the dynamic coupling effect between the connecting links can be ignored, the dimension of observation matrix is low and easy to calculate, but the system dynamic model needs to be established repeatedly, and the cumulative error of parameters is always large [9]. While "unified identification" strategy, i.e. all joints moved, sampled and calculated at the same time, and then all dynamic parameters are acquired at one time. This kind of method is simple to operate and can comprehensively consider various disturbance factors in the actual work of the robot.

To sum up, there are still some deficiencies in the identification methods of dynamic parameters at present. In terms of parameter estimation methods, the least square method is still the most practical and classic method. In the identification strategy, there are many problems, such as large cumulative error, low identification accuracy, complex process, etc. The appropriate joint motion combination form can be found from the distribution characteristics of joint torques.

In this paper, a unified identification approach is proposed considering friction model based on the minimum inertia

* This work is supported by the National Natural Science Foundation of China No. 51705163.

Xiaojun Ding, Jin Hou, Haoyuan Yi, Bin Han and Xin Luo are with State Key Laboratory of Digital Manufacturing Equipment and Technology, Huazhong University of Science and Technology. (Xin Luo is the corresponding author, mexinluo@hust.edu.cn)

978-1-7281-6321-5/19//$31.00 ©2019 IEEE

parameter model. Firstly, the Butterworth filter is used to process the sampled signals, Fourier series is employed for the excitation trajectory, and the optimal excitation trajectory is obtained by observing the minimum number of matrix conditions. Secondly, a reasonable joint velocity threshold is set to remove the joint velocity signals with low speed, and the minimum parameter set is obtained by using the least square method. Finally, the identification results are verified on a 6-DOF industrial manipulator. Experiments show that the proposed dynamic identification method is effective.

The remainder of this paper is organized as follows: In section II, the identification model of manipulator is described. In section III, the dynamic parameters identification process is designed, including excitation trajectory design, parameter estimation, sampling signal processing and model verification. Section IV presents the experimental validations. Finally, the conclusion is drawn in section V.

II. IDENTIFICATION MODEL

Newton-Euler or Lagrange equations is used to obtain the dynamic equation of a serial n -dgrees-of-freedom (DOF) robot

$$\boldsymbol{\tau}_{\text{dyn}} = \mathbf{M}(q)\ddot{q} + \mathbf{C}(q,\dot{q}) + \mathbf{G}(q) \tag{1}$$

where, q , $\dot{q}$ and $\ddot{q}$ are $(n\times 1)$ joint positions, velocities and joint accelerations vectors respectively, $\mathbf{M}(q)$ is the robot $(n\times n)$ inertial matrix, $\mathbf{C}(q,\dot{q})$ is the $(n\times 1)$ centrifugal force and Coriolis force vector, $\mathbf{G}(q)$ is the $(n\times 1)$ gravity vector, $\boldsymbol{\tau}_{\text{dyn}}$ is the $(n\times 1)$ joint torque vector , using centroid parameter [10] or modified Newton-Euler parameter [11], (1) is expressed as a linear form of inertial parameter after parameter transformation

$$\boldsymbol{\tau}_{\text{dyn}} = \boldsymbol{\Phi}_{\text{dyn}}(q,\dot{q},\ddot{q})\boldsymbol{\theta}_{\text{dyn}} \tag{2}$$

where $\boldsymbol{\theta}_{\text{dyn}}$ is the $(10n\times 1)$ inertia parameter vector, $\boldsymbol{\Phi}_{\text{dyn}}$ is the $(n\times 10n)$ observation matrix, the linear characteristic of robot joint torque greatly simplifies the parameter identification process. In addition, the robot needs to consume amount of electromagnetic torque due to friction in the movement process, so the influence of friction must be considered. However, as far as we know, due to the nonlinearity of friction, there is still no accurate model to describe it. Therefore, the classical coulomb friction and viscous friction models are still used here, i.e. the friction torque of joint i is

$$\tau_{\text{fi}} = f_{ci}\,\text{sign}(\dot{q}_i) + f_{\text{vi}}\dot{q}_i \tag{3}$$

where τ_{fi} is the friction torque, f_{ci} are the coulomb friction coefficients, f_{vi} are the viscous friction coefficients. Combining (2) and (3) to obtain a complete linear equation of robot inertial parameters

$$\boldsymbol{\tau} = \boldsymbol{\Phi}_s(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}})\boldsymbol{\theta}_s \tag{4}$$

where $\boldsymbol{\tau}$ is the $(n\times 1)$ motor torque vector , $\boldsymbol{\Phi}_s$ is the $(n\times 12n)$ observation matrix, $\boldsymbol{\theta}_s$ is the $(12n\times 1)$ inertial parameter vector, the inertia parameter vector of the link i can be expressed as

$$\theta_s^i = \left(I_{xxi}, I_{xyi}, I_{xzi}, I_{yyi}, I_{yzi}, I_{zzi}, m_i r_{xi}, m_i r_{yi}, m_i r_{zi}, m_i, f_{ci}, f_{vi}\right)^T \tag{5}$$

where, $I_{xxi}, I_{xyi}, I_{xzi}, I_{yyi}, I_{yzi}, I_{zzi}$ denote the terms of the inertia tensor of the link i relative to the origin of the frame i , $m_i r_{xi}, m_i r_{yi}, m_i r_{zi}$ denote the first-order mass moment of the link i relative to the origin of the frame i (r denotes the centroid position vector), m_i denotes the mass of link i .

Since the observation matrix calculated by (4) is not a full rank matrix, not every inertial parameter has an effect on the torque, only some inertial parameters have an effect on the robot dynamics. Therefore, in the dynamic equation, it is necessary to recombine some inertial parameters through a certain linear relationship or to eliminate some inertial parameters by using simple closed form rules to obtain a minimum set of inertial parameters. The dynamic model containing only the minimum inertial parameters can be expressed as

$$\boldsymbol{\tau} = \boldsymbol{\Phi}(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}})\boldsymbol{\theta} \tag{6}$$

where $\boldsymbol{\Phi}(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}})$ is the $n\times(p+2n)$ observation matrix, $\boldsymbol{\theta}$ is the $(p+2n)$ inertia parameter vector, includes the minimum inertia parameter of the robot links and friction parameter. p and $2n$ are the number of minimum inertia parameters of the robot links and friction parameters respectively. The number of minimum inertia parameters p of the rotating joint robot can be obtained as [12]

$$n_{\min} = 7n_{R1} + 3n_{R2} + n_{R3} \tag{7}$$

where n_{R1} is the number of rotating joints from 0 to $i-1$ that are not parallel to joint i , n_{R2} is the number of axes from 0 to $i-1$ that are parallel or coincident with joint i , and the parallel axis must exist. n_{R3} is the number of axes from joint 0 to $i-1$ are coincide with joint i . In addition, the observation matrix can be calculated by the software package OpenSYMORO [12].

III. THE IDENTIFICATION PROCEDURE

A. Excitation Trajectory Design

Factors such as unmolded error and noise of measured data deteriorate the identification accuracy. In general, the design of excitation trajectory mainly considers two aspects: 1) whether the trajectory can provide accurate and fast parameter estimation under the condition of interference and 2) whether the processing of collected data is simple enough and the identification result is accurate enough. In this paper, we use the finite Fourier series to describe the excitation trajectory proposed by Swevers [13]. The angular position q_i , velocity $\dot{q}_i$ and acceleration $\ddot{q}_i$ for joint i of a n-DOF robot are written as

$$q_i(t)=\sum_{l=1}^{N_i}\frac{a_l^i}{\omega_f l}\sin\left(\omega_f lt\right)-\frac{b_l^i}{\omega_f l}\cos\left(\omega_f lt\right)+q_{i0}$$
$$\dot{q}_i(t)=\sum_{l=1}^{N_i}a_l^i\cos\left(\omega_f lt\right)+b_l^i\sin\left(\omega_f lt\right) \tag{8}$$
$$\ddot{q}_i(t)=\sum_{l=1}^{N_i}-a_l^i\omega_f l\sin\left(\omega_f lt\right)+b_l^i\omega_f l\cos\left(\omega_f lt\right)$$

with ω_f the fundamental pulsation of the Fourier series. This Fourier series specifies a periodic function $T_f=2\pi/\omega_f$, N_i represents the number of harmonic terms of Fourier series. Each Fourier series contains $2N_i+1$ parameters, i.e., the DOF of trajectory optimization, a_l^i and b_l^i, for $i=1$ to N_i, i.e. the amplitudes of the cosine and sine functions, q_{i0} represents the offset on the position trajectory. Trajectory optimization is constrained by joint position, velocity, acceleration, and workspace, as well as velocity of the end effector, etc. Therefore, the excitation trajectory optimization problem based on the condition number optimization criterion can be described as

$$\begin{cases}\min\operatorname{cond}(\mathbf{\Phi})\\ q_{\min}\leqslant q(\beta)\leqslant q_{\max}\\ \left|\dot{q}(\beta)\right|\leqslant\dot{q}_{\max}\\ \left|\ddot{q}(\beta)\right|\leqslant\ddot{q}_{\max}\\ Z_{\min}\leqslant Z_{ee}\leqslant Z_{\max}\\ v\leqslant v_{\max}\\ \omega\leqslant\omega_{\max}\end{cases} \tag{9}$$

with $q_{\min}$, $q_{\max}$, $\dot{q}_{\max}$ and $\ddot{q}_{\max}$ are joint minimum position, maximum position, maximum velocity and maximum acceleration respectively, $Z_{\max}$ and $Z_{\min}$ denote the maximum and minimum height of the end effector relative to the ground respectively, $v_{\max}$ and $\omega_{\max}$ denote the maximum linear velocity and maximum angular velocity of the end effector respectively. The optimization problem described in (9) can be solved by the optimization function "FMINCON" in MATLAB.

B. Parameter Estimation Method

When a robot tracks the excitation trajectory repeatedly, the joint positions and torques at n time instants $t_1,t_1,\ldots t_N$ $\left(nN>p+2n\right)$ have been sampled so as to obtain a statically indeterminate linear equation

$$\tau_N=\begin{bmatrix}\tau\left(t_1\right)\\ \tau\left(t_2\right)\\ \vdots\\ \tau\left(t_n\right)\end{bmatrix}=\begin{bmatrix}\mathbf{\Phi}\left(q\left(t_1\right),\dot{q}\left(t_1\right),\ddot{q}\left(t_1\right)\right)\\ \mathbf{\Phi}\left(q\left(t_2\right),\dot{q}\left(t_2\right),\ddot{q}\left(t_2\right)\right)\\ \vdots\\ \mathbf{\Phi}\left(q\left(t_n\right),\dot{q}\left(t_n\right),\ddot{q}\left(t_n\right)\right)\end{bmatrix}\boldsymbol{\theta}=\mathbf{\Phi}_N\boldsymbol{\theta} \tag{10}$$

with $\mathbf{\Phi}_N$ the $\left(n\times N\times p\right)$ observation matrix (for 6R manipulator $\mathbf{\Phi}_N\in R^{6\times N\times p}$), τ_N is the $\left(n\times N\times 1\right)$ torque vector of (for 6R manipulator $\tau_N\in R^{6\times N\times 1}$) N is the number of data sampling points, (10) is a statically indeterminate linear equation, which is generally solved by least square method or weighted least square method. In this paper, since there are free of noise in measuring the joint position signal, and assuming that the standard deviation of torque measurement noise of all actuators are the same, we still use the least square method to implement it, namely

$$\hat{p}=\left(\Phi^T\Phi\right)^{-1}\Phi^T\tau \tag{11}$$

C. Sampling Signal Processing

In general, the sampled signal will contain different levels of noise, especially in parameter identification, the signals of joint position and torque need to be collected. Thus, the appropriate signal processing methods need to be adopted to obtain the real state and torque value of the joint, thus improving the accuracy of parameter identification. From the introduction, since joint velocity and acceleration are estimated by analytical method, accurate joint position information is a prerequisite. In this paper, a 5-th order low-pass digital Butterworth filter is used to filter and smooth the sampled joint positions and joint torques to improve the signal-to-noise ratio and data quality. In order to obtain a more accurate differential state of joints, the angular velocity and angular acceleration signals are obtained by analytical method [14] which concrete steps are as follows: 1) fitting filtered joint position data into Fourier series by using the least square method and 2) derivation of fitted Fourier series to obtain joint velocity and acceleration. Besides, in order to reduce the influence of friction with low-speed and ensure a better identification accuracy, we set a speed threshold to remove the measured joint speed signals with low-speed, and select the screened joint position information and its corresponding torque, and calculate the minimum set of parameter.

D. Model Verification

The flow of model experiment verification is shown in Fig. 1. Firstly, the minimum set of inertial parameter p of the manipulator is obtained through a set of optimized excitation trajectories (where τ_{me} is measurement torque of excitation trajectory) combined with the least square method. Secondly, with the given verification trajectory information (include the joint position, velocity and acceleration) and the estimated minimum set of parameter p, the estimated torque of verification trajectory of each joint τ_{pr} is obtained by using (6) . Finally, the difference between measured torque of verification trajectory $\tau_{me}^{'}$ and estimated torque of verification trajectory τ_{pr} is compared by the residual root mean square (RMS) , to verify the accuracy of the model.

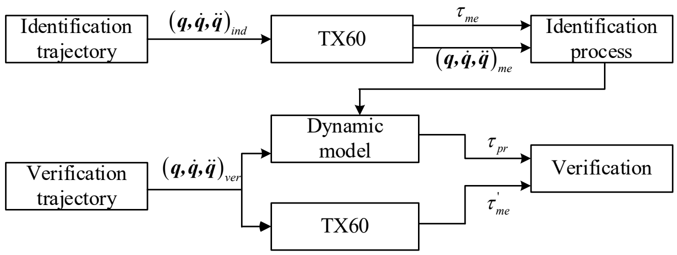


Fig.1 Flow chart of experimental verification

$$\mathrm{RMS}=\sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\tau(k)-\tau_{\mathrm{pr}}(k)\right)^2} \tag{12}$$

where $\tau(k)$ is the sampling torque for the k -th of the verification trajectory, $\tau_{\mathrm{pr}}(k)$ is the estimated torque for the k -th of the verification trajectory . Furthermore, in order to evaluate the effectiveness of the identification method, correlation coefficient ρ is introduced

$$\rho=\frac{\sum_{k=1}^{M}\left(\tau(k)-\overline{\tau}\right)\left(\tau_{pr}(k)-\overline{\tau}_{pr}\right)}{\sqrt{\sum_{k=1}^{M}\left(\tau(k)-\overline{\tau}\right)^2}\sqrt{\sum_{k=1}^{M}\left(\tau_{pr}(k)-\overline{\tau}_{pr}\right)^2}} \tag{13}$$

with $\overline{\tau}$, $\overline{\tau}_{pr}$ the average torques of τ'_{me} and τ_{pr} respectively, when $\rho\to 1$, it indicates that the estimated torque is close to the measured torque, while when $\rho\to 0$, it indicates that the estimated torque is not related to the measured torque.

IV. ANALYSIS OF EXPERIMENTAL RESULTS

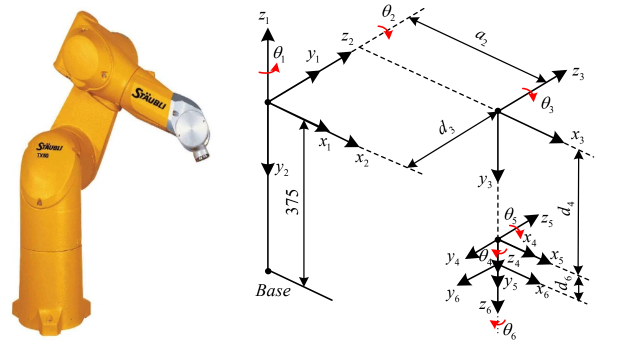
The 6-DOF industrial manipulator Staubli TX-60 has been used in this experiment shown in Fig. 2(a), and its corresponding link frames are shown in Fig. 2(b). The link parameters of the robot are given in Table I.

In the experiment, the fundamental frequency of the trajectories was set to 0.1 Hz (The period is 10 s) and the order of Fourier series was set to 5, i.e., 11 parameters are needed to be optimized for each trajectory. The bandwidth was 0.25 Hz, and the sampling frequency of the data was 250 Hz, i.e., each trajectory period has 2500 sampling data. In order to obtain more accurate dynamic parameters, the parameter estimation was experimented $N_s=10$ times for the optimal excitation trajectory shown in Fig. 3. And the mean value of $\overline{\theta}$ (shown in Table III, where subscript r denotes the grouped parameters) and the standard deviation σ_e of the estimated minimum set of inertial parameters $\hat{\theta}_j$ are given, namely

$$\overline{\theta}_i=\frac{1}{N_s}\sum_{j=1}^{N_s}\hat{\theta}_{ij} \tag{14}$$

$$\sigma_{ei}^2=\frac{1}{N_s-1}\sum_{j=1}^{N_s}\left(\theta_{ij}-\overline{\theta}_i\right)^2,\quad i=1\sim 48. \tag{15}$$

where subscript i denotes the i -th element of the parameter vector, subscript j denotes the j -th estimate of the parameter vector.



(a) (b)

Fig. 2 (a) A 6-DOF industrial manipulator TX-60 (b) Link frames of the robot

Table I. Link parameters of the Staubli TX-60

i	α_i-1	a_i-1	d_i	θ_i
1	0	0	0	θ_1
2	$-\pi/2$	0	0	θ_2-$\pi/2$
3	0	a_2=290mm	d_3=20mm	θ_3-$\pi/2$
4	$-\pi/2$	0	d_4=310mm	θ_4
5	$\pi/2$	0	0	θ_5
6	$-\pi/2$	0	d_6=70mm	θ_6

The motion constraints of the robot are shown in Table II, which is described in (9).

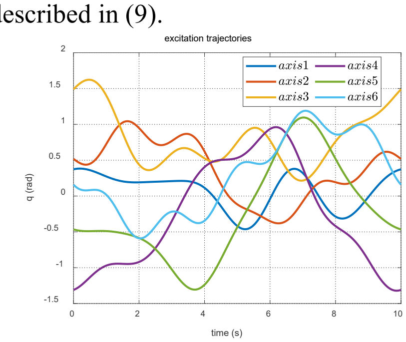


Fig.3 The optimal excitation trajectory of robot obtained from minimum condition number

Fig. 4 shows the measured torque, estimated torque and the estimation residue of six joints of the manipulator respectively. In addition, Table IV shows the effects of identification, i.e. the estimation RMS and correlation coefficient ρ . Observing the curve, when the measuring torque is close to 0, the estimation residual of torque measurement appears a spike due to the effect of friction, which indirectly proves the effectiveness of the adopted algorithm. By analyzing RMS and correlation coefficient, it can be seen that the measurement residual of all axes torque of the robot is relatively small, especially the effect of axis 1, 3, 4 and 5 are beneficial, which correlation coefficient are 0.9916, 0.9460, 0.9815 and 0.9668 respectively. The estimation residual of axis 2 is slightly larger, which may be caused by its large mass, inaccurate friction model and other unknown factors. Also, the effect of axis 6 is a bit poorer than other axes may be caused by its small mass. In order to improve the identification accuracy, the identification strategy need to be improved according to the torque contribution characteristics of each joint of the robot, e.g., "one by one identification" may be used in a combination with this algorithm.

Table II. The motion constraints of each joint of the robot

Para-meters	joint	min	Max	Para-meters	joint	min	Max
	1	-2.6	2.6		1	/	69.8
	2	-2.1	2.1		2	/	69.8
	3	-2.1	2.1		3	/	69.8
q	4	-1.74	-1.74	$\ddot{q}$	4	/	69.8
	5	-1.74	-1.74		5	/	69.8
rad	6	-4.36	4.36	rad/s^2	6	/	69.8
	1	-5.23	5.23		v_x	/	2
	2	-5.23	5.23		v_y	/	2
	3	-6.97	6.97		v_z	/	2
$\dot{q}$	4	-8.72	8.72	$\dot{r}_{end}$	ω_x	/	60
	5	-10.46	10.46		ω_y	/	60
rad/s	6	-17.44	17.44		ω_z	/	60
Z_{ee} /m	/	0.2	/				

Table III. The identified minimum sets of parameters

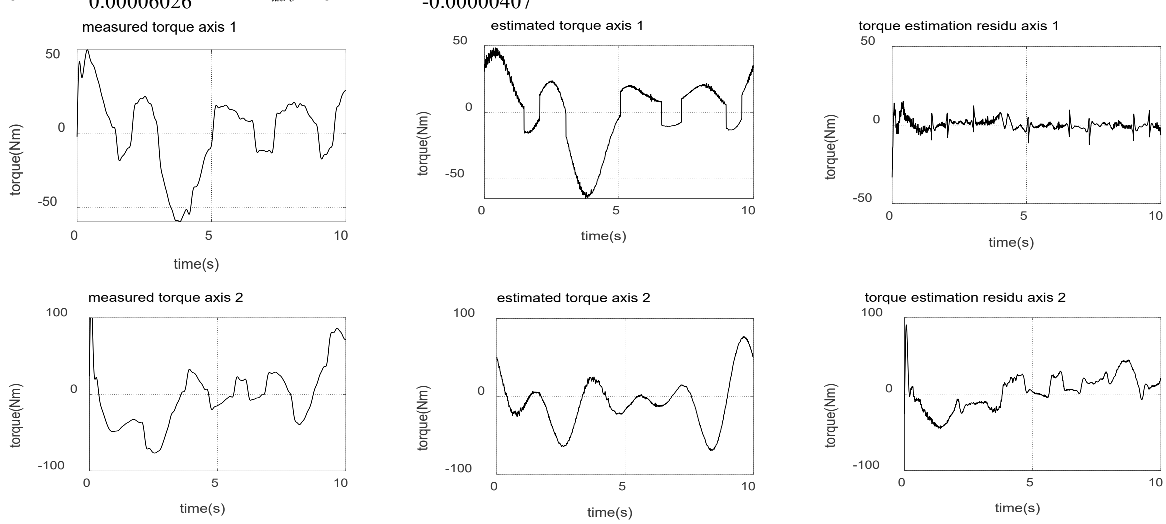
parameters	Identification value	parameters	Identification value
I_{zzr1} / kg•m^2	0.04321749	$m_3 r_{x3}$ / kg•m	-0.00007316
I_{xxr2} / kg•m^2	0.00011890	$m_3 r_{yr3}$ / kg•m	-0.00003898
I_{xy2} / kg•m^2	-0.00005448	Ia_3 / kg•m^2	0.00001347
I_{xz2} / kg•m^2	0.00001574	I_{xxr4} / kg•m^2	-0.00000520
I_{yz2} / kg•m^2	0.00001514	I_{xy4} / kg•m^2	0.00003434
I_{zzr2} / kg•m^2	0.19433783	I_{xz4} / kg•m^2	0.00001264
$m_2 r_{xr2}$ / kg•m	-0.02840552	I_{yz4} / kg•m^2	0.00015267
$m_2 r_{y2}$ / kg•m	-0.07866784	I_{zzr4} / kg•m^2	0.00009299
I_{xxr3} / kg•m^2	0.00020267	$m_4 r_{x4}$ / kg•m	-0.00001283
I_{xy3} / kg•m^2	-0.00002137	$m_4 r_{yr4}$ / kg•m	-0.00000220
I_{xz3} / kg•m^2	0.00002862	Ia_4 / kg•m^2	-0.00001949
I_{yz3} / kg•m^2	0.00006026	I_{xxr5} / kg•m^2	-0.00000407
I_{zzr3} / kg•m^2	-0.02466123	I_{xy5} / kg•m^2	-0.00000685
I_{xz5} / kg•m^2	-0.00001448	Ia_6 / kg•m^2	0.00361501
I_{yz5} / kg•m^2	-0.00004171	f_{c1} / N•m	8.78771015
I_{zzr5} / kg•m^2	0.00002194	f_{v1} / N•m•s•rad^{-1}	0.27721979
$m_5 r_{x5}$ / kg•m	-0.00000127	f_{c2} / N•m	-0.63765100
$m_5 r_{yr5}$ / kg•m	-0.00000712	f_{v2} / N•m•s•rad^{-1}	0.29601563
Ia_5 / kg•m^2	-0.00000525	f_{c3} / N•m	6.74296618
I_{xxr6} / kg•m^2	0.00001158	f_{v3} / N•m•s•rad^{-1}	0.14146487
I_{xy6} / kg•m^2	0.00000707	f_{c4} / N•m	2.70550530
I_{xz6} / kg•m^2	0.00002757	f_{v4} / N•m•s•rad^{-1}	0.03098004
I_{yz6} / kg•m^2	0.00001885	f_{c5} / N•m	3.63556095
I_{zz6} / kg•m^2	0.05113364	f_{v5} / N•m•s•rad^{-1}	0.04879572
$m_6 r_{x6}$ / kg•m	0.00250705	f_{c6} / N•m	0.18253124
$m_6 r_{y6}$ / kg•m	0.00199335	f_{v6} / N•m•s•rad^{-1}	0.02397583

Table IV. The RMS and correlation coefficient

RMS	3.4320	22.3964	5.3226	0.8863	1.7324	1.5140
ρ	0.9916	0.8252	0.9460	0.9815	0.9668	0.7536

V. CONCLUSION

This paper presents a unified identification approach of dynamic parameters considering friction model. The 5-th order Fourier series is used as the excitation trajectory, the optimal excitation trajectory is obtained by minimizing the minimum condition number, and the minimum set of dynamic parameters is obtained by combining the least square method. The effectiveness of the identification approach is demonstrated by observing the estimation RMS and correlation coefficient ρ of each joint. In order to improve the identification accuracy, it is essential to have a deep analysis on the contribution characteristics of joint torque of the robot.



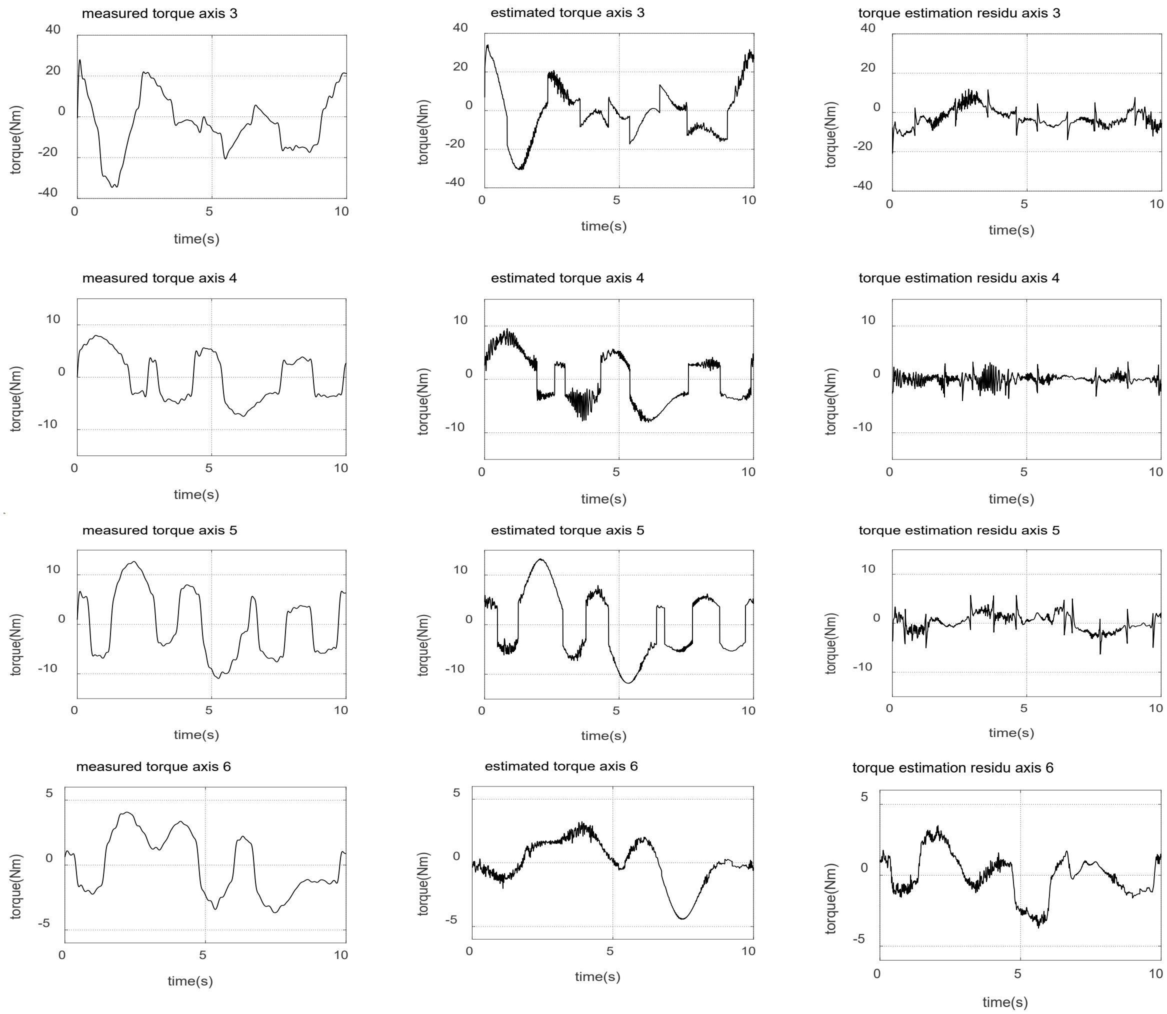


Fig. 4 Measured torque, estimated torque, and estimation residue

REFERENCES

[1] Wu J, Wang J, You Z. "An overview of dynamic parameter identification of robots," Robotics and computer-integrated manufacturing, vol. 26, no. 5, pp. 414-419, Mar.2018.

[2] X. Ding, Y. Liu, J. Hou and Q. Ma, "Online Dynamic Tip-Over Avoidance for a Wheeled Mobile Manipulator With an Improved Tip-Over Moment Stability Criterion," in IEEE Access, vol. 7, pp. 67632-67645, May.2019.

[3] Qin Z, Baron L, Birglen L. "A new approach to the dynamic parameter identification of robotic manipulators," Robotica, vol. 26, no. 5, pp. 539-547, Jul.2010.

[4] J. Swevers, W. Verdonck and J. De Schutter, "Dynamic Model Identification for Industrial Robots," in IEEE Control Systems Magazine, vol. 27, no. 5, pp. 58-71, Oct. 2007.

[5] Gautier M, Poignet P. "Extended Kalman filtering and weighted least squares dynamic identification of robot," Control Engineering Practice, vol. 9, no. 12, pp. 1361-1372, Dec. 2001.

[6] Olsen M M, Swevers J, Verdonck W. "Maximum likelihood identification of a dynamic robot model: Implementation issues," The international Journal of robotics research, vol. 21, no. 2, pp. 89-96, Feb. 2002.

[7] Yan D, Lu Y, Levy D. "Parameter identification of robot manipulators: A heuristic particle swarm search approach," PloS one, vol. 10, no. 6, pp. 129-157, Jun. 2015.

[8] Q. Zhu and S. Mao, "Inertia parameter identification of robot arm based on BP neural network," Proceedings of the 33rd Chinese Control Conference, Nanjing, Jul. 2014, pp. 6605-6609.

[9] Ya-dong D, Bai C, Hong-tao W. "An identification method of industrial robot's dynamic parameters," Journal of South China University of Technology (Natural Science Edition), vol. 43, no.3, pp. 49-56, Mar. 2015.

[10] A. Calanca, L. M. Capisani, A. Ferrara and L. Magnani, "MIMO Closed Loop Identification of an Industrial Robot," in IEEE Transactions on Control Systems Technology, vol. 19, no. 5, pp. 1214-1224, Sept. 2011.

[11] Khosla P K. "Estimation of robot dynamics parameters: Theory and application," Pittsburgh, PA, USA: Carnegie-Mellon University, 1987, pp. 87-111.

[12] Khalil W, Dombre E. "Modeling, identification and control of robots," London, LON, UK: Kogan Page Science ,2004. pp. 77-121.

[13] J. Swevers, C. Ganseman, D. B. Tukel, J. de Schutter and H. Van Brussel, "Optimal robot excitation and identification," in IEEE Transactions on Robotics and Automation, vol. 13, no. 5, pp. 730-740, Oct. 1997.

[14] Kinsheel A, Taha Z, Deboucha A, et al. "Robust least square estimation of the CRS A465 robot arms dynamic model parameters," Journal of Mechanical Engineering Research, vol. 4, no.3, pp. 88-89, Mar. 2012.