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Parameter identification for industrial robots with a fast and robust trajectory design approach

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ABSTRACT

Model-based, torque-level control can offer precision and speed advantages over velocity-level or position-level robot control. However, the dynamic parameters of the robot must be identified accurately. Several steps are involved in dynamic parameter identification, including modeling the system dynamics, joint position/torque data acquisition and filtering, experimental design, dynamic parameters estimation and validation. In this paper, we propose a novel, computationally efficient and intuitive optimality criterion to design the excitation trajectory for the robot to follow. Experiments are carried out for a 6 degree of freedom (DOF) Staubli TX-90 robot. We validate the dynamics parameters using torque prediction accuracy and compare to existing methods. The RMS errors of the prediction were small, and the computation time for the new, optimal objective function is an order of magnitude less than for existing approaches.

1. Introduction

Contemporary applications of robot arms demand high precision and speed, e.g. advanced manufacturing [1] and multi-robot system control [2]. These applications typically require advanced model-based control algorithms or control algorithms based on torque input [3]. Such control schemes require accurate knowledge of the dynamic parameters of robot arm. However, many robot manufacturers do not provide these parameters or provide only partial information [4,5]. Experimental identification or calibration is therefore the only reliable approach to obtain this information.

Many models of robot dynamics have been proposed in the context of dynamic parameter identification. Gautier suggested the energy identification model in [6] and the power model in [7]. The main advantage of these models is that they depend only on functions of joint position and velocity. Researchers have employed inverse dynamic models of robot arms to identify dynamic parameters [5,8–10]. Inverse dynamic models provide more information than the energy or the power model. This additional information allows the creation of well-conditioned over-determined regressor matrices.

There are several ways to estimate the dynamic parameters. Least squares estimation methods [6,11] and maximum likelihood estimation methods [9] are popular approaches. Other approaches include the extended Kalman filter in [12], the total least squares is developed in [13], the online recursive total least squares estimation method in [14], the weighted least squares estimation method [15,16], nonlinear least squares optimization [8], and the instrumental variable approach developed in [17]. Generally, joint angle and torque/current data can be measured directly, but joint velocity and acceleration must be estimated. There are several approaches to estimate velocity and acceleration, including observer/estimators, zero-phase band pass filter, low-pass filters and Kalman filters [6,8,18].

Designing an excitation trajectory is an essential and significant part of improving estimation accuracy. A fifth-order polynomial trajectory in joint space was proposed as an excitation trajectory in [19]. To enable repeatable identification experiments and improve the signal to noise ratio, periodic excitation trajectories based on Fourier series [9], modified Fourier series [5] and finite sum of harmonic sine functions [20] have been proposed. Two optimality criteria have been popular to find optimal periodic trajectories. One is based on minimization of the condition number of the regressor matrix [5,20,21]; another is based on minimization of $\mathbf{log}\{\mathbf{det}(\cdot)\}$ of the Fisher information matrix [20,9]. Since each Fourier series contains $2\times N_i+1$ parameters [22], it can be difficult to solve the optimization problem. Each Fourier series must meet constraints on the trajectory such as initial and final conditions and bounds on position, velocity and acceleration.

Model validation is also an important procedure for confirming the parameter estimation results. Experiment results can directly demonstrate the identification result [9]. Janot et al. discussed the importance of statistical analysis in validating results [17].

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A primary contribution of this paper is a novel, simple and intuitive optimal criterion to design the exciting trajectory. Our approach reduces the number of terms that define the trajectory, and we employ Hadamard's inequality, which states that the determinant of a positive definite matrix is less than or equal to the product of its diagonal entries, thus simplifying the optimization problem. For a $m \times n$ rectangular matrix W, the complexity of calculating the upper bound of the determinate using Hadamard's is $O(n)$, but the complexity of calculating the determinate of $W^T W$ is $O(mn^2+n^3)$ and the complexity of calculating the condition number of W is $O(mn^2)$. The use of Hadamard's inequality offers a great reduction in complexity and calculation time in finding the optimal parameters.

We compare our outcome with the two popular optimization functions in terms of computational complexity. Our proposed trajectory performs as well as those found by the existing optimization functions in terms of root mean squared error, and requires an order of magnitude less computation time. We use our algorithm to determine the dynamic parameters of the Staubli TX-90 robot manipulator. To our knowledge, the parameters of this robot have not previously been determined, and this represents a second major contribution of this paper.

The remainder of this paper is organized as follows. Section 2 introduces the background information regarding our experimental dynamic calibration methods. Section 3 describes the proposed excitation trajectory and new optimality criterion. Section 4 provides simulation results that verify the proposed estimation algorithm. Finally, the conclusion is given in Section 5.

2. Background

Our approach employs the inverse dynamic model and the least squares (LS) estimation method to estimate inertia parameters of robot arm. We also use a zero-phase low pass filter to process position data and velocities are calculated with a central difference algorithm. Accelerations are calculated with the central difference algorithm and followed by smoothing, which is performed by the Robust LOcal polynomial regrESSion (RLOESS) smoother [23]. RLOESS has gained widespread acceptance in statistics as an appealing solution for fitting smooth curves to noisy data. The overall procedure of identification is illustrated in Fig. 1

2.1. Dynamic identification model

The dynamic model of an n-link rigid robot can be derived using the Euler–Lagrange or the Newton–Euler formulation [24]. The mathematical model in joint space [25] is given by

$$M(q)\ddot{q}+C(q,\dot{q})\dot{q}+\tau_f=\tau \tag{1}$$

where $q(t)=[q_1(t),\ q_2(t),\dots,q_n(t)]^T \in \mathbb{R}^n$ is a vector of joint position, and $\dot{q}(t)\in\mathbb{R}^n$ and $\ddot{q}(t)\in\mathbb{R}^n$ are the joint velocity and the acceleration vectors, respectively. $M(q)\in\mathbb{R}^{n\times n}$ is the mass or inertia matrix of the robot, $C(q,\dot{q})$ contains Coriolis, centrifugal and gravitational force terms, $\tau_f(t)\in\mathbb{R}^n$ is the friction forces, and $\tau(t)\in\mathbb{R}^n$ represents the joint torque vector, which is the input to the system. We model the friction forces as

$$\tau_f=f_v\dot{q}+f_c\,\mathrm{sgn}(\dot{q}) \tag{2}$$

where f_v and f_c are constant $n\times n$ diagonal matrices representing viscous and Coulomb friction parameters, respectively, and $\mathrm{sgn}(\cdot)$ is the sign function.

The modified Denavit and Hartenberg (MDH) convention [26] allows us to rewrite the mathematical model (1) in a linearly parametrized form [24] with N_s standard parameters:

$$\tau=\mathrm{Y}_s(q,\dot{q},\ddot{q})\beta_s \tag{3}$$

where $\mathrm{Y}_s(q,\dot{q},\ddot{q})\in\mathbb{R}^{n\times N_s}$ is a regressor matrix and $\beta_s\in\mathbb{R}^{N_s\times 1}$ is a vector of standard parameters. For rigid robots, there are 13 standard parameters by each link and joint, including the six components of the inertia matrix of link j at the origin of frame j $(I_{xxj},I_{xyj},I_{xzj},I_{yyj},I_{yzj},I_{zzj})$, the first moments of link j (mx_j,my_j,mz_j), the mass (m_j) of link j, the total inertia moment (Ia_j) for rotor and gears of actuator j and viscous and Coulomb friction coefficients (f_{vj},f_{cj}) [27].

The base parameters are the minimal set of identifiable parameters to parametrize the dynamic equation. They are obtained by regrouping some of the standard parameters by means of linear relations [11,28] or a numerical method with respect to the QR decomposition [29]. Then the dynamics equation with N_b identifiable base parameters can be addressed as

$$\tau=\mathrm{Y}(q,\dot{q},\ddot{q})\beta \tag{4}$$

where $\beta\in\mathbb{R}^{N_b}$ are the base parameters and $\mathrm{Y}(q,\dot{q},\ddot{q})\in\mathbb{R}^{n\times N_b}$ is a subset of the independent columns of Y_s [30].

An excitation reference trajectory must be used to persistently excite the given system. In this work, we employ a periodic trajectory. Assume that the joint positions and motor torques are measured at a sampling frequency of ω_s, and denote the kth sampling time as t_k. If the fundamental frequency of the trajectories is w_f, we can collect $M=\omega_s/w_f$ samples over one period T. These measurements can be used to obtain an over-determined set of equations [31]:

$$\mathbf{\Gamma}=\mathrm{W}\beta+\rho \tag{5}$$

where

$$\mathrm{W}=\begin{bmatrix}\mathrm{Y}(q(t_1),\dot{q}(t_1),\ddot{q}(t_1))_{n\times N_b}\\ \mathrm{Y}(q(t_2),\dot{q}(t_2),\ddot{q}(t_2))_{n\times N_b}\\ \vdots\\ \mathrm{Y}(q(t_M),\dot{q}(t_M),\ddot{q}(t_M))_{n\times N_b}\end{bmatrix}$$

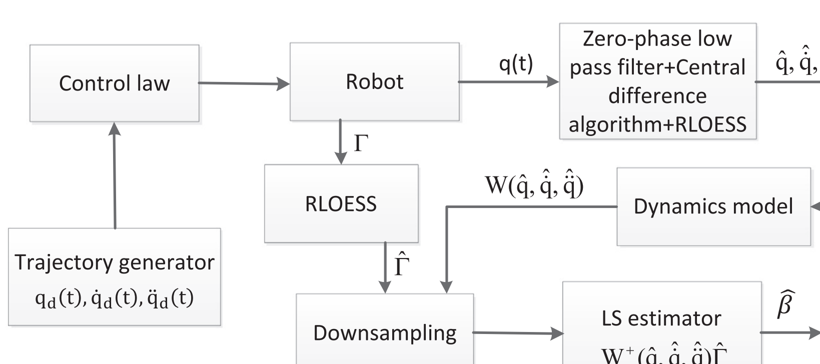

Fig. 1. The proposed parameter identification process.