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An instrumental variable approach for rigid industrial robots identification

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ABSTRACT

This paper deals with the important topic of rigid industrial robots identification. The usual identification method is based on the use of the inverse dynamic model and the least-squares technique. In order to obtain good results, a well-tuned derivative bandpass filtering of joint positions is needed to calculate the joint velocities and accelerations. However, we can doubt whether the bandpass filter is well-tuned or not. Another approach is the instrumental variable (IV) method which is robust to data filtering and which is statistically optimal. In this paper, an IV approach relevant for identification of rigid industrial robots is introduced. The set of instruments is the inverse dynamic model built from simulated data which are calculated from the simulation of the direct dynamic model. The simulation assumes the same reference trajectories and the same control structure for both the actual and the simulated robot and is based on the previous IV estimates. Furthermore, to obtain a rapid convergence, the gains of the simulated controller are updated according to IV estimates. Thus, the proposed approach validates the inverse and direct dynamic models simultaneously and is not sensitive to initial conditions. The experimental results obtained with a 2 degrees of freedom (DOF) planar prototype and with a 6 DOF industrial robot show the effectiveness of our approach: it is possible to identify 60 parameters in 3 iterations and in 11 s.

1. Introduction

The usual robots identification method is based on the use of the inverse dynamic model (IDM) and the least-squares technique (LS). This method, called as Inverse Dynamic Identification Model with Least Squares technique (IDIM-LS) has been validated on several industrial robots, see Khalil and Dombre (2002), Swevers, Verdonck, and De Schutter (2007), Hollerbach, Khalil, and Gautier (2008), and Gautier, Janot, and Vandanjon (2012) and the references given therein. In order to obtain good results, a well-tuned derivative bandpass filtering of joint positions is needed to calculate the joint velocities and accelerations. However, even with the guidelines given in Gautier et al. (2012) to tune the bandpass filter, the users can doubt whether the IDIM-LS estimates are unbiased or not.

This leads us to try other methods: the Total Least Square (TLS) (Gautier, Vandanjon, & Presse, 1994;Gautier & Briot, 2012; Xi, 1995), the Extended Kalman Filter (EKF) (Gautier & Poignet, 2001; Kostic, de Jager, Steinbuch, & Hensen, 2004, the Set Membership Uncertainty (Ramdani & Poignet, 2005), an algorithm based on Linear Matrix Inequality (LMI) tools (Calafiore & Indri, 2000a), a maximum likelihood (ML) approach (Olsen & Petersen, 2001; Olsen, Swevers, & Verdonck, 2002. Though these approaches are interesting, they do not really improve the IDIM-LS method coupled with an appropriate bandpass filtering, their robustness to data quality and/or data filtering is not addressed and some of them are quite time consuming.

Another approach is the Instrumental Variable technique (IV) which was introduced by Reiersøl in 1941 (Reiersøl, 1941). This method deals with the problem of noisy observation matrix and can be statistically optimal. In Söderstrom and Stoica (1989), Garnier and Wang (2008), Young (2011), and Gilson, Garnier, Young, and Van den Hof (2011) and the references given therein, different IV methods are studied for linear systems. However, these works are theoretical-oriented and they are validated on low-dimensional systems. This may explain why there are few real-world applications of IV method (Garnier, Gilson, Young, & Huselstein, 2007; Liu, Yao, & Gao, 2009 and especially in robotics (Puthenpura & Shina, 1986; Vandanjon, Janot, Gautier, & Khatounian, 2007; Xi, 1995; Yoshida, Ikeda, & Mayeda, 1992. This shows that a gap must be bridged between the theory and control engineering practices.

In this paper, an IV approach which is relevant for the identification of rigid industrial robots is proposed. The set of instruments is the inverse dynamic model built from simulated data which are calculated from the simulation of the direct dynamic model. The simulation assumes the same reference trajectories and the same

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control structure for both the actual and the simulated robot and is based on the previous IV estimates. In addition, in order to obtain a valid set of instruments, the gains of the simulated controller are updated according to the IV estimates. This algorithm called as IDIM-IV method validates the inverse and direct dynamic models simultaneously, improves the noise immunity of estimates with respect to corrupted data in the observation matrix and has a rapid convergence.

A condensed version of this work has been presented in Janot, Vandanjon, and Gautier (2009, 2012). However, the theoretical proofs are missing, the tuning of control-loops is missing, the gains update of the simulated controller is not well introduced and the statistical efficiency of the IDIM-IV method is not addressed. In this paper, the detailed proofs to enlighten the theoretical understanding of the IDIM-IV method and additional experimental results are given. At last, the statistical efficiency of the IDIM-IV method is experimentally addressed.

The rest of the paper is organized as follows: Section 2 reviews the usual identification technique of robots dynamic parameters. Section 3 presents the IDIM-IV identification method. SCARA prototype robot and experimental results are presented in Section 4 while TX40 robot and experimental results are presented in Section 5. Finally, Section 6 is the conclusion.

2. IDIM-LS method: inverse dynamic identification model and least squares method

2.1. Inverse dynamic model of robots

The inverse dynamic model (IDM) of n-moving-links robots calculates the $(n \times 1)$ vector of joint torques τ_{idm} as a function of generalized coordinates and their derivatives (Khalil & Dombre, 2002). It is given by

$$\boldsymbol{\tau}_{idm} = \mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{N}(\mathbf{q}, \dot{\mathbf{q}}), \tag{1}$$

where $\mathbf{q}$, $\dot{\mathbf{q}}$ and $\ddot{\mathbf{q}}$ are respectively the $(n \times 1)$ vectors of generalized joint positions, velocities and accelerations, $\mathbf{M}(\mathbf{q})$ is the $(n \times n)$ inertia matrix, $\mathbf{N}(\mathbf{q}, \dot{\mathbf{q}})$ is the $(n \times 1)$ vector of centrifugal, Coriolis, gravitational and friction torques.

The modified Denavit and Hartenberg (DHM) notation allows obtaining an IDM linear in relation to a set of base parameters $\boldsymbol{\beta}$ (Khalil & Dombre, 2002)

$$\boldsymbol{\tau}_{idm} = \mathbf{IDM}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\boldsymbol{\beta}, \tag{2}$$

where $\mathbf{IDM}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$ is the $(n \times b)$ matrix of basis functions of body dynamics and $\boldsymbol{\beta}$ is the $(b \times 1)$ vector of base parameters.

The base parameters are the minimum number of dynamic parameters from which the IDM can be calculated. They are obtained from standard dynamic parameters by eliminating those which have no effect on the IDM and by regrouping some of them with linear relations (Gautier & Khalil, 1990; Mayeda, Yoshida, & Osuka, 1990. The standard parameters of a link j are XX_j, XY_j, XZ_j, YY_j, YZ_j and ZZ_j the six components of the inertia matrix of link j at the origin of frame j, MX_j, MY_j and MZ_j the components of the first moment of link j, M_j the mass of link j, Ia_j the total inertia moment for rotor and gears of actuator j, Fv_j and Fc_j the viscous and Coulomb friction parameters of joint j.

Because of uncertainties (measurement noise, model mismatch …), the $(n \times 1)$ vector of actual joint torques $\boldsymbol{\tau}$ differs from $\boldsymbol{\tau}_{idm}$ by an error $\mathbf{e}$ i.e.

$$\boldsymbol{\tau} = \boldsymbol{\tau}_{idm} + \mathbf{e} = \mathbf{IDM}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\boldsymbol{\beta} + \mathbf{e}. \tag{3}$$

Eq. (3) represents the Inverse Dynamic Identification Model (IDIM). The offline identification of base parameters $\boldsymbol{\beta}$ is considered, given the measured or estimated offline data for $\boldsymbol{\tau}$ and $(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$, collected while the robot is tracking some planned trajectories.

2.2. Data acquisition

Usually, data available from controllers of robots are the measurements of $\mathbf{q}$ and the measurements of $\mathbf{v}_\tau$ the $(n \times 1)$ vector of control signals.

Usually, robots are position-controlled and the proportional-derivative (PD), the proportional-integral-derivative (PID), the computed torque (flatness control) and the passive controls are the laws which are often applied (Khalil & Dombre, 2002). When identifying the base parameters, the PD control is preferred to the others because it is easy to tune and an excellent tracking is not necessary (Gautier et al., 2012).

At last, the motors are current-controlled with a proportional-integral (PI) control. The current closed-loop has a bandwidth greater than 500 Hz. Then, within the frequency range of body dynamics (less than 10 Hz), the transfer function of the current closed-loop is modeled as a static gain (Gautier et al., 2012).

The joint torques are calculated from the control signals with the following relation

$$\boldsymbol{\tau} = \mathbf{G}_\tau \mathbf{v}_\tau, \tag{4}$$

where $\mathbf{G}_\tau$ is the $(n \times n)$ diagonal matrix of drive gains. The diagonal components of $\mathbf{G}_\tau$ have *a priori* values given by manufacturers. These values can be checked with special tests, see e.g. Gautier and Briot (2012).

2.3. Data filtering

In (3), $\mathbf{q}$ is estimated with $\hat{\mathbf{q}}$ obtained by filtering the measurements of $\mathbf{q}$ through a low-pass Butterworth filter in both the forward and the reverse directions using *filtfilt* Matlab function. This filter has a flat amplitude characteristic without phase shift in the range $[0\ \omega_{fq}]$, ω_{fq} being the filter cutoff frequency. We choose $\omega_{fq} \geq 5\boldsymbol{\omega}_{dyn}$, ω_{dyn} being the maximum bandwidth of the joint position-loop (Gautier et al., 2012). $(\hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}})$ are calculated offline without phase shift using a central differentiation algorithm of low-pass filtered positions $\hat{\mathbf{q}}$. In doing so, the distortion is avoided while the coefficients of $\mathbf{IDM}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$ are calculated (Gautier et al., 2012).

The IDIM given by (3) is sampled at a measurement frequency f_m while the robot is tracking reference trajectories $(\mathbf{q}_r, \dot{\mathbf{q}}_r, \ddot{\mathbf{q}}_r)$. We obtain an over-determined linear system of n_m equations and b unknowns given by

$$\mathbf{Y}_{fm}(\boldsymbol{\tau}) = \mathbf{W}_{fm}(\hat{\mathbf{q}}, \hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}})\boldsymbol{\beta} + \boldsymbol{\rho}_{fm}, \tag{5}$$

where $\mathbf{Y}_{fm}(\boldsymbol{\tau})$ is the $(n_m \times 1)$ sampled vector of $\boldsymbol{\tau}$, $\mathbf{W}_{fm}(\hat{\mathbf{q}}, \hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}})$ is the $(n_m \times b)$ sampled matrix of $\mathbf{IDM}(\hat{\mathbf{q}}, \hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}})$, $\boldsymbol{\rho}_{fm}$ is the $(n_m \times 1)$ sampled vector of $\mathbf{e}$.

$\boldsymbol{\tau}$ is perturbed by high-frequency disturbances that are rejected by the closed-loop control. These torque ripples are eliminated by using a parallel decimation procedure which low-pass filters in parallel $\mathbf{Y}_{fm}$ and each column of $\mathbf{W}_{fm}$ and resamples them at a lower rate, keeping one sample over n_d. This parallel decimation is carried out with *decimate* Matlab function. In (6), the low-pass filter cutoff frequency $\omega_{fp} = 2\pi * 0.8 f_m/(2n_d)$ is tuned to keep $\mathbf{Y}$ and $\mathbf{W}(\hat{\mathbf{q}}, \hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}})$ within the same frequency range of dynamics. According to Gautier et al. (2012) a good choice is $\omega_{fp} \geq 2\omega_{dyn}$.

After data acquisition and the parallel decimation of (5), we obtain the following over-determined linear system

$$\mathbf{Y}(\boldsymbol{\tau}) = \mathbf{W}(\hat{\mathbf{q}}, \hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}})\boldsymbol{\beta} + \boldsymbol{\rho}, \tag{6}$$

where $\mathbf{Y}(\boldsymbol{\tau})$ is the $(r \times 1)$ measurements vector built from actual torques $\boldsymbol{\tau}$, $\mathbf{W}(\hat{\mathbf{q}}, \hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}})$ is the $(r \times b)$ observation matrix built from