Control Engineering Practice 74 (2018) 107–117

Contents lists available at ScienceDirect

Control Engineering Practice

journal homepage: www.elsevier.com/locate/conengprac

An improved instrumental variable method for industrial robot model identification

M. Brunot[a,b,*], A. Janot[a], P.C. Young[c,d], F. Carrillo[b]

[a] ONERA, 2 Avenue Edouard Belin, 31055 Toulouse, France.
[b] LGP ENI Tarbes, 47 avenue d'Azereix, BP 1629, 65016 Tarbes, France
[c] Systems and Control Group, Lancaster Environment Centre, Lancaster University, UK
[d] Integrated Catchment Assessment and Management Centre, Fenner School of Environment & Society, Australian National University College of Medicine, Biology & Environment, Canberra, Australia

ARTICLE INFO

Keywords:
Refined instrumental variable
Closed-loop system identification
Robot identification
Inverse dynamics
Dynamic parameters
Robot dynamics

ABSTRACT

Industrial robots are electro-mechanical systems with double integrator behaviour, necessitating operation and model identification under closed-loop control conditions. The Inverse Dynamic Identification Model (IDIM) is a mechanical model based on Newton's laws that has the advantage of being linear with respect to the parameters. Existing Instrumental Variable (IDIM-IV) estimation provides a robust solution to this estimation problem and the paper introduces an improved IDIM-PIV method that takes account of the additive noise characteristics by adding prefilters that provide lower variance estimates of the IDIM parameters. Inspired by the prefiltering approach used in optimal Refined Instrumental Variable (RIV) estimation, the IDIM-PIV method identifies the nonlinear physical model of the robot, as well as the noise model resulting from the feedback control system. It also has the advantage of providing a systematic prefiltering process, in contrast to that required for the previous IDIM-IV method. The issue of an unknown controller is also considered and resolved using existing parametric identification. The evaluation of the new estimation algorithms on a six degrees-of-freedom rigid robot shows that they improve statistical efficiency, with the controller either known or identified as an intrinsic part of the IDIM-PIV algorithm.

1. Introduction

Robots are mechanical systems that have a double integrator behaviour and they must be identified, therefore, while operating in closed-loop. Their direct and inverse dynamic models are formulated in continuous time and are calculated from Newton's laws or the Lagrange equations (Khalil & Dombre, 2004). The method based on the inverse dynamic identification model (IDIM) and least squares estimation (LS) is the standard procedure to identify the dynamic parameters of robots. This approach, termed IDIM-LS, has been successfully applied to identify the dynamic parameters of several prototypes and industrial robots (see Briot & Gautier, 2015; Calanca, Capisani, Ferrara, & Magnani, 2011; Khosla & Kanade, 1985; Olsen, Swevers, & Verdonck, 2002; Raucent, Campion, Bastin, Samin, & Willems, 1992; Swevers, Ganseman, Tukel, De Schutter, & Van Brussel, 1997; Wu, Wang, & Wang, 2008 among others). Good results can be obtained provided that an appropriate derivative bandpass filtering of the joint positions is used in order to calculate the joint velocities and accelerations. However, even with the guidelines for tuning the bandpass filtering given in Gautier (1997), the user can doubt whether the IDIM-LS estimates are consistent or not because robots are identified while they are operating in closed loop while it is known that the LS estimates are biased in this case (Van den Hof, 1998).

Other identification methods have been evaluated: the Total Least Squares method (Hollerbach & Nahvi, 1997; Xi, 1995); the Extended Kalman Filter (Gautier & Poignet, 2001; Kostic, De Jager, Steinbuch, & Hensen, 2004); the Set Membership Uncertainty (Ramdani & Poignet, 2005); an algorithm based on LMI tools in Calafiore and Indri (1999); a ML approach (Dolinskỳ & Čelikovskỳ, 2017; Olsen et al., 2002); the closed-loop output error (Gautier, Janot, & Vandanjon, 2013; Östring, Gunnarsson, & Norrlöf, 2003); a Bayesian approach (Ting, Mistry, Peters, Schaal, & Nakanishi, 2006); a method which estimates the nonlinear effects in the frequency domain (Wernholt & Gunnarsson, 2008); the Unscented Kalman Filter (Dellon & Matsuoka, 2009); an algorithm based on neural network (Soewandito, Oetomo, & Ang, 2011). In Calanca et al. (2011), the authors suggest to complete the IDIM-LS method with deeper statistical analyses; while in Miranda-Colorado and Moreno-Valenzuela (2017), the authors propose an improvement to the standard approach by using an algebraic technique for state estimation

* Corresponding author at: ONERA, 2 Avenue Edouard Belin, 31055 Toulouse, France
E-mail address: Mathieu.Brunot@onera.fr (M. Brunot).

https://doi.org/10.1016/j.conengprac.2018.02.010
Received 13 September 2017; Received in revised form 23 January 2018; Accepted 22 February 2018
Available online 23 March 2018
0967-0661/

and a procedure based on the Semi-Definite Programming (Wensing, Kim, & Slotine, 2018). An overview of some of these methods is given by Wu, Wang, and You (2010). Although all these techniques are of great interest, they do not really improve the IDIM-LS method, even when combined with the derivative bandpass filtering, because the LS estimates are still asymptotically biased. Also, the robustness against data filtering has not been studied; and some of these approaches have not been validated on a 6 DOF industrial robot. Except for the approach presented in Gautier, Janot, et al. (2013), only the direct or inverse dynamic model is validated and the condition that the columns of the observation matrix are not correlated with the error terms is not addressed, even though it is a critical condition to obtain consistent estimates, see e.g. Young (2011).

An approach able to provide consistent estimates while the system is identified in closed loop is the instrumental variables (IV) technique introduced by Reiersøl (1941). In the system identification community, IV methods have been studied extensively; see e.g. Young (1981, 1970, 2011) for continuous time systems; and (Jakeman & Young, 1979; Rowe, 1970; Söderström & Stoica, 1983; Wong & Polak, 1967; Young, 1976, 2011) for discrete time systems. One interesting feature of the optimal Refined IV approach to both continuous (RIVC) and discrete-time (RIV) model identification (Young, 2015) is the use of an optimal prefiltering process which takes into account the noise model and so provides statistically efficient estimates (i.e. with minimum variance). Furthermore, for systems identified in closed-loop, specific techniques are able to deal with an unknown controller: see e.g. Gilson, Garnier, Young, and Van den Hof (2011) and Young (2011). Although these methods are appealing, they were developed primarily for Linear Time Invariant (LTI) systems and so cannot be applied straightforwardly to complex, nonlinear robot systems. This may explain why there are few applications in robotics (see e.g. Puthenpura & Sinha, 1986; Xi, 1995; Yoshida, Ikeda, & Mayeda, 1993). A first attempt to bridge the gap between robotics and automatic control was made in Janot, Vandanjon, and Gautier (2014a) where a generic IV approach relevant for the identification of rigid industrial robots was proposed. The set of instruments is the IDM constructed from simulated data calculated from the simulation of the DDM. The simulation of the direct dynamic model assumes the same reference trajectories and the same control structure for both the actual and the simulated robots and is based on the previous IV estimates. This algorithm, termed the 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. Despite the good results obtained, the statistical efficiency of the IDIM-IV estimates is not addressed, the relationships that exist between the IDIM-IV approach and the approaches in automatic control are not emphasised and the controller is assumed to be known to the user.

The aim of this paper is twofold. First, we show how a prefiltering process inspired by RIVC identification can be introduced into the IDIM-IV identification algorithm for robot system identification, so establishing links between the robotic and the automatic control approaches to identification. The resulting IDIM-PIV method extends the work undertaken in Brunot, Janot, Carrillo, and Garnier (2017), where the IDIM-IV residuals are statistically analysed, and in Janot, Young, and Gautier (2017), where the joint velocities and accelerations are estimated with a state space estimation technique. Secondly, the issue of identifying the IDIM model in the presence of an unknown controller is addressed by a parametric identification. Practical validation of this new algorithm is carried by experiments conducted on a six Degrees-Of-Freedom (DOF) industrial robot arm, Stäubli TX40.

The paper is organised as follows. The next section provides the background to robot system architecture, including the models, control laws and sensors used in the analysis and control of robot systems, as well as the notation used in such analysis. Section 3 summarises the standard techniques for robot identification and the use of prefilters in IV algorithms. In the fourth section, the proposed prefiltering process and the method of controller identification are described. The results of experiments are summarised in Section 5; and finally, the concluding remarks are provided in Section 6.

2. Robot system architecture

2.1. Robot dynamic models

The Inverse Dynamic Model (IDM) of a rigid robot with n moving links is the expression of the $(n \times 1)$ torque vector, $\boldsymbol{\tau}_{idm}$, as a function of the joint positions and their derivatives (Khalil & Dombre, 2004). The following relationship is derived by application of Newton's law or the Lagrangian equations:

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

where $\boldsymbol{M}$ is the $(n \times n)$ inertia matrix; $\boldsymbol{N}$ is the $(n \times 1)$ vector of centrifugal, Coriolis, gravitational, and friction torques; and $\boldsymbol{q}_{nf}$, $\dot{\boldsymbol{q}}_{nf}$, $\ddot{\boldsymbol{q}}_{nf}$ are, respectively, the $(n \times 1)$ noise-free vectors of joint positions, velocities and accelerations. According to Gautier (1986), a joint j of an industrial robot has 14 standard parameters:

$$\begin{aligned}\chi_j = [XX_j \quad XY_j \quad XZ_j \quad YY_j \quad YZ_j \quad ZZ_j \\ MX_j \quad MY_j \quad MZ_j \quad M_j \quad Ia_j \quad F_{v_j} \quad F_{c_j} \quad \tau_{off_j}]^T\end{aligned} \tag{2}$$

where XX_j, XY_j, XZ_j, YY_j, YZ_j and ZZ_j are the six components of the inertia matrix at the origin of frame j; MX_j, MY_j, MZ_j are the three components of the first moments; M_j is the mass of link j; Ia_j is the total inertia moment for rotor and gears of the actuator; F_{v_j} and F_{c_j} are, respectively, the viscous and Coulomb friction coefficients; τ_{off_j} is an offset parameter containing the asymmetry of the Coulomb friction with respect to the sign of the velocity and the current amplifier offset which supplies the motor.

Since some of these parameters have no effect on the dynamic model, while others are regrouped with linear relations, we obtain a $(b \times 1)$ vector of base dynamic parameters: $\boldsymbol{\theta}$; see Gautier (1991). In addition, the IDM is linear with respect to the base parameters and so we obtain the following linear relation

$$\boldsymbol{\tau}_{idm}(t) = \boldsymbol{\phi}\left(\boldsymbol{q}_{nf}(t), \dot{\boldsymbol{q}}_{nf}(t), \ddot{\boldsymbol{q}}_{nf}(t)\right)\boldsymbol{\theta} = \boldsymbol{\phi}_{nf}(t)\boldsymbol{\theta}, \tag{3}$$

where $\boldsymbol{\phi}$ is the $(n \times b)$ matrix of basis functions (from hereon referred to as the 'observation matrix'). It is worth noting that base parameters are simply referred to as model parameters in Marconato, Schoukens, Rolain, and Schoukens (2013). Each element of $\boldsymbol{\phi}$ is a basis function of the body dynamics. These basis functions can be nonlinear relationships involving the positions, velocities and accelerations and the nature of these nonlinearities can be estimated, if this is required, using the approach suggested in Janot et al. (2017).

As a result of inevitable measurement noise and modelling errors, the actual torque $\boldsymbol{\tau}$ differs from $\boldsymbol{\tau}_{idm}$ by an error $\boldsymbol{v}$, so that the usual definition of the Inverse Dynamic Identification Model (IDIM) is given by

$$\boldsymbol{\tau}(t) = \boldsymbol{\tau}_{idm}(t) + \boldsymbol{v}(t) = \boldsymbol{\phi}\left(\boldsymbol{q}_{nf}(t), \dot{\boldsymbol{q}}_{nf}(t), \ddot{\boldsymbol{q}}_{nf}(t)\right)\boldsymbol{\theta} + \boldsymbol{v}(t). \tag{4}$$

The associated DDM relates the joint accelerations to a *nonlinear* function of the states (positions and velocities) and the parameters: e.g.,

$$\ddot{\boldsymbol{q}}_{nf}(t) = \boldsymbol{M}\left(\boldsymbol{q}_{nf}(t)\right)^{-1}\left(\boldsymbol{\tau}_{idm}(t) - \boldsymbol{N}\left(\boldsymbol{q}_{nf}(t), \dot{\boldsymbol{q}}_{nf}(t)\right)\right). \tag{5}$$

2.2. Control laws

As pointed out previously, robots need to operate within a closed-loop control system due to their double integrator behaviour. In particular, the joint positions are controlled within two nested loops: an inner-loop for the current control and an outer-loop for the position control. Most often the control laws are simple Proportional Derivative (PD), Proportional Integral Derivative (PID), or computed torque and passive control (see Chapter 14 in Khalil & Dombre, 2004 for details on this topic). In the present paper, it is assumed that the controller is linear; that each link is controlled separately from the others; and that there is