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A revised Durbin-Wu-Hausman test for industrial robot identification

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ABSTRACT

This paper addresses the topic of robot identification. The usual identification method makes use of the inverse dynamic model (IDM) and the least squares (LS) technique while robot is tracking exciting trajectories. Assuming an appropriate bandpass filtering, good results can be obtained. However, the users are in doubt whether the columns of the observation matrix (the regressors) are uncorrelated (exogenous) or correlated (endogenous) with the error terms. The exogeneity condition is rarely verified in a formal way whereas it is a fundamental condition to obtain unbiased LS estimates. In Econometrics, the Durbin-Wu-Hausman test (DWH-test) is a formal statistic for investigating whether the regressors are exogenous or endogenous. However, the DWH-test cannot be straightforwardly used for robot identification because it is assumed that the set of instruments is valid. In this paper, a Revised DWH-test suitable for robot identification is proposed. The revised DWH-test validates/invalidates the instruments chosen by the user and validates the exogeneity assumption through the calculation of the QR factorization of the augmented observation matrix combined with a *F*-test if required. The experimental results obtained with a 6 degrees-of-freedom (DOF) industrial robot validate the proposed statistic.

1. Introduction

The usual robot identification method makes use of the continuous-time inverse dynamic model and the least squares (LS) technique while the robot is tracking some exciting trajectories. This explains why robot identification belongs to the closed-loop identification of continuous-time models from sampled data. This method, called as Inverse Dynamic Identification Model with Least Squares method (IDIM-LS), has been successfully applied to identify the inertial parameters of several prototypes and industrial robots, (Olsen, Swevers, & Verdonck, 2002; Swevers, Verdonck, & De Schutter, 2007; Hollerbach, Khalil, & Gautier, 2008; Calanca, Capisani, Ferrara, & Magnani, 2011; Gautier, Janot, & Vandanjon, 2013; Janot, Vandanjon, Gautier, 2014a) among others. Good results are obtained provided that an appropriate bandpass filtering of the joint positions is used to calculate the joint velocities and accelerations. However, because robots are identified in closed loop, the users can doubt whether the columns of the observation matrix (the regressors) are correlated with the error terms (endogenous) or not (exogenous) even with a data filtering, see e.g. Söderström and Stoica (1989), Garnier and Wang (2008), Young (2011), Gilson, Garnier, Young, and Van den Hof (2011).

Other identification methods were tried: the Total Least-Squares (Xi, 1995), the Set Membership Uncertainty (Ramdani & Poignet, 2005), an algorithm based on Linear Matrix Inequality (LMI) tools (Indri, Calafiore, Legnani, Jatta, & Visioli, 2002), a maximum likelihood (ML) approach (Olsen et al., 2002), the Closed-Loop Output-Error method (Landau, 2001; Östring, Gunnarsson, & Norrlöf, 2003; Gautier et al., 2013), an algorithm based on neural network (Soewandito, Oetomo, Ang, 2011), a Bayesian approach (Ting, Mistry, Peters, Schaal, & Nakanishi, 2006), the extended Kalman filter (Gautier & Poignet, 2001) and (Kostic, de Jager, Steinbuch, & Hensen, 2004), a method which estimates the nonlinear effects in the frequency domain (Wernholt & Gunnarsson, 2008) and the Unscented Kalman Filter (Dellon & Matsuoka, 2009). Although all these techniques are of interest, they do not really improve the IDIM-LS method combined with an appropriate data filtering. Furthermore, the robustness against data filtering was not studied, some of these approaches were not validated on a 6 degrees-of-freedom (DOF) industrial robot and the condition that the regressors are not correlated with the error terms is not addressed whereas it is a critical condition to obtain unbiased estimates (Hausman, 1978; Davidson & MacKinnon, 1993; Wooldridge, 2009). This condition is called as the exogeneity condition.

The Instrumental Variable method (IV) provides unbiased estimates while the regressors are endogenous (Söderström & Stoica,

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1989; Garnier & Wang, 2008; Young, 2011). A generic IV method for industrial robots identification is proposed in Janot et al. (2014a), Janot, Vandanjon, and Gautier (2014b). This approach called as the IDIM-IV method was successfully validated on a 2 DOF prototype robot and on a 6 DOF industrial robot. However, the validity of the instruments was not addressed and using the IV method while the regressors are exogenous provides inefficient unbiased estimates i.e. their variances are not minimal (Hausman, 1978; Davidson & MacKinnon, 1993; Wooldridge, 2009).

In Econometrics, the Durbin-Wu-Hausman test (DWH-test) is a formal statistic for investigating whether the regressors are exogenous or endogenous (Hausman, 1978). The DWH-test makes use of the Two Stages Least Squares (2SLS) technique and an augmented LS regression. However, the DWH-test cannot be straightforwardly used for robot identification because it is implicitly assumed that the instrumental matrix is well correlated with the observation matrix and uncorrelated with the errors. Furthermore, the econometric models are empirical whereas the models used in mechanical engineering are based on physical laws (e.g. the Newton's laws).

In this paper, it is proposed to bridge the gap between Econometrics theory and Control engineering practice by presenting a Revised DWH-test suitable for identification of robots. This revisited statistic validates/invalidates the model chosen by the user and the exogeneity condition is validated by the QR factorization of the augmented observation matrix combined with the *F*-test.

A condensed version of this work has been presented in Janot, Vandanjon, and Gautier (2013). This paper contains detailed proofs to enlighten the theoretical understanding of the Revised DWH-test, heteroskedasticity is taken into account and additional experimental results are provided.

The rest of the paper is organized as follows. Section 2 recalls the IDIM-LS method and reviews the theory of Econometrics. Section 3 introduces the Revised DWH-test while Section 4 is devoted to experimental results. Finally, Section 5 concludes the paper.

2. Theoretical background: modeling, identification of robots and introduction of the DWH-test

2.1. Modeling and identification of robots

The inverse dynamic model (IDM) of robot with n moving links calculates the $(n \times 1)$ joint torques vector $\boldsymbol{\tau}_{idm}$ as a function of generalized coordinates and their derivatives (Khalil & Dombre, 2002),

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

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 (MDH) notation allows to obtain an IDM which is linear in relation to a set of base parameters $\boldsymbol{\beta}$

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

where $\mathbf{IDM}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$ is the $(n \times b)$ matrix of basis functions of bodies 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 the standard dynamic parameters by regrouping some of them with linear relations (Mayeda, Yoshida, & Osukaet, 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 a total inertia moment for rotor and gears of actuator j; Fv_j and Fc_j the viscous and Coulomb friction parameters of joint j.

The direct dynamic model (DDM) of robots is given by

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} = \boldsymbol{\tau}_{idm} - \mathbf{N}(\mathbf{q}, \dot{\mathbf{q}}). \tag{3}$$

Proportional–Derivative (PD) and Proportional–Integral–Derivative (PID) controls are often implemented to identify the dynamic parameters. The joint j signal control v_{τ_j} is given by

$$v_{\tau_j} = C_j(s)\left(q_{r_j} - q_{mes_j}\right), \tag{4}$$

where $C_j(s)$ is the transfer function of the joint j controller, q_{r_j} is the joint j position reference, q_{mes_j} is the measurement of q_j the joint j position, s is the time derivative operator i.e. $s = d/dt$.

The data available from robots controllers are $\mathbf{q}_{mes}$ the $(n \times 1)$ vector of measurements of $\mathbf{q}$ and $\mathbf{v}_\tau$, the $(n \times 1)$ vector of control signals. Each joint j torque is connected with each joint j control signal ν_{τ_j} by

$$\tau_j = g_{\tau_j}\nu_{\tau_j}, \tag{5}$$

where g_{τ_j} is the joint j drive gain *a priori* given by manufacturers.

In (2), $\mathbf{q}$ is estimated with $\hat{\mathbf{q}}$ obtained by filtering $\mathbf{q}_{mes}$ through a lowpass Butterworth filter in both the forward and reverse directions. $(\hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}})$ are calculated with a central differentiation algorithm of $\hat{\mathbf{q}}$. $\boldsymbol{\tau}$ being perturbed by high-frequency disturbances, a parallel decimation procedure is used to eliminate torque ripples (see Gautier et al., 2013 for the details).

Because of uncertainties, the $(n \times 1)$ vector of the actual joint torques $\boldsymbol{\tau}$ differs from $\boldsymbol{\tau}_{idm}$ by an error $\mathbf{e}$. The model (2) is sampled while the robot is tracking trajectories (see Gautier et al., 2013 for the details). After data acquisition and data filtering, the following overdetermined linear system is obtained

$$\mathbf{y}(\boldsymbol{\tau}) = \mathbf{X}\left(\hat{\mathbf{q}}, \hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}}\right)\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{6}$$

where $\mathbf{y}(\boldsymbol{\tau})$ is the $(r \times 1)$ measurements vector built from the actual torques $\boldsymbol{\tau}$; $\mathbf{X}(\hat{\mathbf{q}}, \hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}})$ is the $(r \times b)$ observation matrix built from the sampling of $\mathbf{IDM}(\hat{\mathbf{q}}, \hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}})$; $\boldsymbol{\varepsilon}$ is the $(r \times 1)$ sampled vector of $\mathbf{e}$; $r = n{\cdot}n_e$ is the number of rows in (6), n_e being the number of rows in a subsystem j.

Relation (6) is the Inverse Dynamic Identification Model (IDIM). The columns of $\mathbf{X}(\hat{\mathbf{q}}, \hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}})$ are the regressors. $\boldsymbol{\varepsilon}$ is assumed to have zero mean, to be serially uncorrelated with a covariance matrix $\boldsymbol{\Omega}$ partitioned so that $\boldsymbol{\Omega} = diag(\sigma_1^2\mathbf{I}_{ne} \ \cdots \ \sigma_j^2\mathbf{I}_{ne} \ \cdots \ \sigma_n^2\mathbf{I}_{ne})$, $\mathbf{I}_{n_e}$ being the $(n_e \times n_e)$ identity matrix. σ_j^2 is estimated through the Ordinary Least Squares (OLS) solution of a subsystem j (see Gautier et al., 2013 for the details). The IDIM-LS estimates and their covariance matrix are given by

$$\hat{\boldsymbol{\beta}}_{LS} = \left(\mathbf{X}^T\boldsymbol{\Omega}^{-1}\mathbf{X}\right)^{-1}\mathbf{X}^T\boldsymbol{\Omega}^{-1}\mathbf{y}, \ \hat{\boldsymbol{\Sigma}}_{LS} = \left(\mathbf{X}^T\boldsymbol{\Omega}^{-1}\mathbf{X}\right)^{-1}. \tag{7}$$

The IDIM-LS estimates are unbiased if

$$E\left(\mathbf{X}^T\boldsymbol{\varepsilon}\right) = \mathbf{0}, \tag{8}$$

where $E(.)$ is the expectation operator (Davidson & MacKinnon, 1993).

Because robots are identified in closed loop, the users can doubt whether $\mathbf{X}(\hat{\mathbf{q}}, \hat{\dot{\mathbf{q}}}, \hat{\ddot{\mathbf{q}}})$ is correlated with $\boldsymbol{\varepsilon}$ or not. To overcome the problem of a correlation between $\mathbf{X}$ and $\boldsymbol{\varepsilon}$, the Two-Stage-Least-Squares (2SLS) technique is an appropriate method.