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# Physical parameter identification of a one-degree-of-freedom electromechanical system operating in closed loop

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**Abstract:** This paper deals with the identification of physical parameters of a one-degree-of-freedom electromechanical system that operates in closed loop. Two models are considered: the inverse dynamic model which is linear in relation to the physical parameters to be identified and the direct dynamic model which is linear in relation to a nonlinear combination of the physical parameters. Three methods are considered and compared: the traditional method which makes use of the inverse dynamic model, tailor-made data prefiltering and the least-squares method, an instrumental variable approach which makes use of the direct and inverse dynamic models and another instrumental variable approach which makes use of the direct dynamic model only. The experimental results show that the instrumental variable method based on the use of the inverse and direct dynamic models seems to be more appropriate than the two others because it is robust against noise and the physical parameters are directly identified.

**Keywords:** closed-loop identification, robot identification, physical parameters, instrumental variable

## 1. INTRODUCTION

Dynamic models used in robotics and in mechanical engineering are continuous-time models that result from Newton's law or Lagrange equations. Mechanical systems having a double-integrator behavior must be identified while they operate in closed loop (Khalil & Dombre 2002) and (Gautier *et al.* 2013). The direct dynamic model (DDM) is rarely used because it is usually nonlinear with respect to the dynamic parameters (Gautier *et al.* 2013). The identification method makes use of the inverse physical model (IDM) which is linear in relation to the dynamic parameters and the Least-Squares (LS) method. Good results can be obtained provided that an appropriate data filtering is used (Gautier *et al.* 2013). However, it is known that simple LS estimates are biased when the system is identified in open or closed loop (Van den Hof 1998), (Gilson *et al.* 2011).

One interesting approach to consistently identify a system in closed loop is the instrumental variable (IV) method (see *e.g.* Young 2011 and the references therein). Interest in IV methods has been growing in recent years. While consistency is generally secured, the main issue for an IV-based method is how should the instrumental variables be chosen to obtain optimal accuracy (Söderström & Stoica 1989), (Gilson *et al.* 2011). Amongst the different proposed solutions, an iterative algorithm where the required prefilter and instruments are iteratively adapted is known to be one of the most reliable (Young 2011). Although the IV method provides good results, the works presented in the previous references are theoretical-oriented. This may explain why the IV method has not yet well penetrated the fields of robotics (Puthenpura

& Sinha 1986), (Janot *et al.* 2014). More recently, the identification of continuous-time models has grown in popularity in the field of Automatic Control (Garnier *et al.* 2007), (Garnier & Wang 2008) and see the recent special issue in the International Journal of Control (Garnier & Young 2014).

The aim of this work is twofold. First, it aims at broadcasting the benefits of the IV method to practitioners in robotics. Secondly, it aims at showing the advantages of using the IDM to identify the physical parameters to the System Identification community. To do so, the identification of two continuous-time dynamic models of a one degree-of-freedom (DOF) electromechanical position unit (EMPS) is considered: the IDM which is linear in relation to the physical parameters and the DDM which is linear with respect to a set of parameters that results from a nonlinear combination of the physical parameters. Because the EMPS depends on 3 dynamic parameters only, the interpretation of the experimental results is easy. The three identification methods compared in this paper are: the LS method which makes use of the IDM combined with a tailor-made data prefiltering, an IV-based method which makes use of the IDM and the DDM presented in (Janot *et al.* 2014), an IV-based approach which makes use of the DDM only. The experimental results show that the IV method based on the use of the IDM and the DDM seems to be more appropriate than the two others to identify the dynamic parameters because it is robust against noises and the physical parameters are directly identified without requiring the tailor-made data filtering which requires some expertise from the practitioner.

The paper is organized as follows: Section 2 describes the two models considered for the EMPS. Section 3 reviews the identification method based on the simple LS technique while Section 4 presents the two proposed IV-based approaches. The experimental results are given in Section 5 and Section 6 gives some concluding remarks.

## 2. MODELS OF THE ELECTROMECHANICAL SYSTEM

### 2.1 Experimental setup

The EMPS is a high-precision linear Electro-Mechanical Positioning System (see Figure 1). It is a standard configuration of a drive system for prismatic joint of robots or machine tools. It is connected to a dSPACE digital control system for easy control and data acquisition using Matlab and Simulink software. Its main components are

- A Maxon DC motor equipped with an incremental encoder. This DC motor is position-controlled with a PD controller.
- A Star high-precision low-friction ball screw drive positioning unit and a load in translation.

All variables and parameters are given in ISO units on the load side.



Fig. 1. EMPS prototype to be identified

### 2.2 Direct dynamic model

The direct dynamic model (DDM) of a robot expresses the acceleration vector as a function of the motor torque, joint position and velocity vector (Khalil & Dombre 2002). From Newton's law, we have

$$M\ddot{q} = \tau_{idm} - F_v \dot{q} - F_c \text{sign}(\dot{q}), \quad (1)$$

where  $q$ ,  $\dot{q}$ ,  $\ddot{q}$  are the joint position, velocity and acceleration in m,  $\text{m}\cdot\text{s}^{-1}$  and  $\text{m}\cdot\text{s}^{-2}$  respectively,  $\tau_{idm}$  is the motor force in N,  $M$  is the mass in Kg,  $F_v$  and  $F_c$  are the viscous and Coulomb friction parameters in  $\text{N}/\text{m}\cdot\text{s}^{-1}$  and in N respectively.

The physical parameters  $M$ ,  $F_v$  and  $F_c$  are called as dynamic parameters. In the case of the EMPS, the DDM is linear with respect to a set of parameters that result from a nonlinear combination of the dynamic parameters

$$\ddot{q} = DDM(q, \dot{q}, \tau_{idm}) \theta_{ddm}, \quad (2)$$

where  $DDM(q, \dot{q}, \tau_{idm}) = \begin{bmatrix} \tau_{idm} & -\dot{q} & -\text{sign}(\dot{q}) \end{bmatrix}$ , is the  $(1 \times 3)$  matrix of basis functions of the DDM and  $\theta_{ddm} = [\theta_1 \ \theta_2 \ \theta_3]^T$  is the  $(3 \times 1)$  vector of the 3 parameters that are nonlinear combination of the 3 dynamic parameters given by  $\theta_1 = 1/M$ ,  $\theta_2 = F_v/M$  and

$$\theta_3 = F_c/M.$$

### 2.3 Inverse dynamic model

The inverse dynamic model (IDM) of a robot expresses  $\tau_{idm}$  as a function of  $q$ ,  $\dot{q}$  and  $\ddot{q}$  (Khalil & Dombre 2002). In the case of the EMPS, the IDM is given by

$$\tau_{idm} = M\ddot{q} + F_v \dot{q} + F_c \text{sign}(\dot{q}), \quad (3)$$

Equation (3) is linear in relation to the dynamic parameters,

$$\tau_{idm} = IDM(q, \dot{q}, \ddot{q}) \theta_{idm}, \quad (4)$$

where  $IDM(q, \dot{q}, \ddot{q}) = \begin{bmatrix} \ddot{q} & \dot{q} & \text{sign}(\dot{q}) \end{bmatrix}$ , is the  $(1 \times 3)$  matrix of basis functions of the IDM and  $\theta_{idm} = \begin{bmatrix} M & F_v & F_c \end{bmatrix}^T$ , is the  $(3 \times 1)$  vector of the 3 dynamic parameters.

Because the DDM is usually nonlinear with respect to the dynamic parameters, it is rarely used for robot identification (Swevers *et al.* 2007, Gautier *et al.* 2013).

### 2.4 Data acquisition

Data that are available are the measurements of  $q$  denoted as  $q_{meas}$  and  $v_{meas}$  the measurement of the control signal denoted as  $v$ . The control signal  $v$  results from the control law and is linked to  $\tau_{idm}$  by the following relation

$$\tau_{idm} = g_\tau v, \quad (5)$$

where  $g_\tau$  is drive gain of the EMPS. Though the drive gain is usually given by the manufacturers, it can be identified with special tests (Gautier & Briot 2014).

In the case of the EMPS, it has been estimated to  $g_\tau = 35.15$  N/V.

### 2.5 Control of the EMPS

Because the EMPS is a system having a pure integrator, it cannot be identified in open loop. It is position-controlled with a Proportional-Derivative (PD). In (Gautier *et al.* 2013), it has been shown that a PD control is enough to identify the dynamic parameters because an excellent tracking is not needed. The control signal  $v$  is given by

$$v = K_p K_v (q_r - q) - K_v \dot{q}, \quad (6)$$

where  $K_p$  is the proportional gain and  $K_v$  is the derivative gain. With (5), it comes out that  $\tau_{idm}$  is given by

$$\tau_{idm} = g_\tau K_p K_v (q_r - q) - g_\tau K_v \dot{q}. \quad (7)$$

The bandwidth of the position loop is 20Hz. This gives  $K_p = 160.18$  1/s and  $K_v = 243.45$  V/m.s<sup>-1</sup>.

### 2.6 Closed-loop block-diagram for the EMPS prototype

The closed-loop block-diagram for the EMPS is shown in Fig. 2, where  $p$  denotes the differentiation operator.

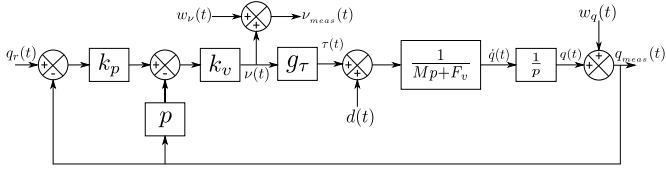


Fig. 2. Closed-loop block-diagram for the EMPS prototype

The measurement noise of the control signal (resp. position) is denoted as  $w_v$  (resp.  $w_q$ ). It is assumed that  $w_v$  and  $w_q$  are uncorrelated, serially independent and homoscedastic with a bounded variance. Those assumptions are usually valid in practice. The EMPS can be modeled as

$$q(t) = G(p)(\tau(t) + d(t)), \quad (8)$$

where  $G(p) = \frac{1}{p} \left( \frac{1}{Mp + F_v} \right)$  and  $d(t) = -F_c \text{sign}(\dot{q})$ .

The Coulomb friction effect is considered as a state-dependent input disturbance while  $G(p)$  is considered as the linear part of the model.

### 3. IDENTIFICATION METHODS BASED ON LEAST-SQUARES METHOD

#### 3.1 Usual LS-based identification method of the IDM

The traditional identification method developed for robots is based on the use of the IDM and the simple Least Squares (LS) method. However, we face here to a closed-loop situation and this requires special treatment, see e.g. (Van den Hof 1998). Here, a pragmatic approach based on an efficient tailor-made data filtering makes it possible to use the simple LS identification methods.

In (3),  $q$  is estimated with  $\hat{q}$  obtained by filtering  $q_{meas}$  through a low-pass filter while  $(\hat{q}, \hat{\dot{q}})$  are calculated with a central differentiation algorithm of  $\hat{q}$ . Details about the data filtering can be found in (Gautier *et al.* 2013). Hence, the actual motor force  $\tau$  differs from  $\tau_{idm}$  by an error  $e_{idm}$  because of model mismatch, measurements noises and data filtering. Then one has

$$\tau = IDM(\hat{q}, \hat{\dot{q}}, \hat{\ddot{q}})\theta_{idm} + e_{idm}. \quad (9)$$

From  $N_s$  available samples of the measured signals observed at discrete-time instants for tracking exciting trajectories  $(q_r, \dot{q}_r, \ddot{q}_r)$ , an over-determined system is obtained

$$y_{idm} = X_{idm}\theta_{idm} + \varepsilon_{idm}, \quad (10)$$

where  $y_{idm}$  is the  $(N_s \times 1)$  sampled vector of  $\tau$ ,  $X_{idm}$  the  $(N_s \times 3)$  matrix of  $IDM(\hat{q}, \hat{\dot{q}}, \hat{\ddot{q}})$ ,  $\varepsilon_{idm}$  is the  $(N_s \times 1)$  vector of  $e_{idm}$  error terms and  $N_s$  is the number of samples.

$\tau$  being perturbed by high-frequency disturbances and since there is no information in high frequencies because of the

lowpass filtered data  $(\hat{q}, \hat{\dot{q}}, \hat{\ddot{q}})$ , a parallel decimation procedure is used to eliminate torque ripples and the samples in high frequencies.

By applying the tailor-made data prefiltering, the filtered regression model is assumed to be free of noise so that simple LS can be used to deliver the following estimates

$$\hat{\theta}_{idm-LS} = (X_{idm}^T X_{idm})^{-1} X_{idm}^T y_{idm}. \quad (11)$$

The unicity of the LS solution (11) is ensured if  $X_{idm}$  is a column-full-rank matrix i.e.  $\text{rank}(X_{idm}) = 3$ . At this step, the trajectories  $(q_r, \dot{q}_r, \ddot{q}_r)$  are assumed to be exciting enough.

The computation of the standard deviation  $\sigma_{\hat{\theta}_{idm_j}}$  and the relative standard derivation  $100 \left| \frac{\sigma_{\hat{\theta}_{idm_j}}}{\hat{\theta}_{idm_j}} \right|$  for  $\hat{\theta}_{idm_j} \neq 0$  presented in (Gautier *et al.* 2013) and (Janot *et al.* 2014) assumes that  $X_{idm}$  is deterministic and are not recalled here.

#### 3.2 LS-based identification of the DDM

Similarly,  $\hat{q}$  differs from  $\ddot{q}$  by an error  $e_{ddm}$ . Then one has

$$\hat{q} = \ddot{q} + e_{ddm} = DDM(\hat{q}, \hat{\dot{q}}, \tau)\theta_{ddm} + e_{ddm}. \quad (12)$$

From  $N_s$  available samples of the measured signals observed at discrete-time instants an over-determined system is obtained

$$y_{ddm} = X_{ddm}\theta_{ddm} + \varepsilon_{ddm}, \quad (13)$$

where  $y_{ddm}$  is the  $(N_s \times 1)$  vector of  $\hat{q}$ ,  $X_{ddm}$  the  $(N_s \times 3)$  matrix of  $DDM(\hat{q}, \hat{\dot{q}}, \tau)$ ,  $\varepsilon_{ddm}$  is the  $(N_s \times 1)$  vector of  $e_{ddm}$  error terms.

A similar tailor-made data prefiltering can be used to make the DDM regression model assume to be free of noise so that the simple LS method can be used to estimate the DDM parameters

$$\hat{\theta}_{ddm-LS} = (X_{ddm}^T X_{ddm})^{-1} X_{ddm}^T y_{ddm}. \quad (14)$$

#### 3.3 Main difference between the IDM and the DDM

Associated to a data prefiltering strategy, the simple linear LS method can be used to estimate the parameters of both DDM and IDM models. For the practitioner, the question is then: shall we use the DDM or the IDM model?

It must be noticed that the physical parameters of the system are directly identified with the IDM. Furthermore, their deviation can be calculated with the usual statistical rules (see e.g. Davidson & MacKinnon 1993). When using the DDM, only  $\theta_{ddm}$  which results from nonlinear combination of the physical parameters is identified. Hence, the deviations of the physical parameters cannot be directly calculated with the classical rules of Statistics.

Because of this reason, it is recommended to use the IDM to identify the parameters of electromechanical systems.

### 3.4 Conclusion

The simple LS-based method was successfully applied on several prototypes and industrial robots (see e.g. Swevers *et al.* 2007, Gautier *et al.* 2013)). However, to provide good results, the joint position and control signal measurements must be accurate enough at high sampling rate and a tailor-made data filtering must be well tuned (Gautier *et al.* 2013) and (Janot *et al.* 2014). This requires some expertise from practitioners. The IV method is an interesting alternative to LS method to overcome those drawbacks.

## 4. INSTRUMENTAL VARIABLE METHOD

The IV method consists in introducing an  $(N_s \times 3)$  instrumental matrix denoted as  $Z$ . When using the IDM (resp. DDM),  $Z$  must be correlated with  $X_{idm}$  (resp.  $X_{ddm}$ ) and uncorrelated with the error  $\varepsilon_{idm}$  (resp.  $\varepsilon_{ddm}$ ). Hence, to be a valid instrumental matrix,  $Z$  must fulfill the following conditions

$$\begin{cases} \text{rank}\left(E\left(Z^T X_{idm}\right)\right) = 3 \\ E\left(Z^T \varepsilon_{idm}\right) = 0 \end{cases}, \begin{cases} \text{rank}\left(E\left(Z^T X_{ddm}\right)\right) = 3 \\ E\left(Z^T \varepsilon_{ddm}\right) = 0 \end{cases}, \quad (15)$$

where  $E(\cdot)$  is the expectation operator.

Assuming that (15) holds, the unbiased IV solutions are given by

$$\hat{\theta}_{IV-idm} = \left(Z_{idm}^T X_{idm}\right)^{-1} Z_{idm}^T y_{idm}, \quad (16)$$

$$\hat{\theta}_{IV-ddm} = \left(Z_{ddm}^T X_{ddm}\right)^{-1} Z_{ddm}^T y_{ddm}. \quad (17)$$

In the last decade, different IV solutions have been developed for closed-loop identification (see e.g. Gilson *et al.*, 2011, Young 2011). Though the IV method is an interesting alternative to LS method for closed-loop identification of continuous-time models, the main issue is the construction of the instruments.

### 4.1 IV-based identification for the IDM

Disregarding the noise model, a simple approach consists in building  $Z$  from simulated data, which are the outputs of an auxiliary model. This auxiliary model is the noise-free model of the system (Young 2011). The simulated data provide an estimate of the noise-free data.

For mechanical systems, it has been shown that a valid auxiliary model is the DDM (Janot *et al.* 2014). The simulation of the DDM is performed with the IV obtained at the previous iteration denoted as  $\hat{\theta}_{IV-idm}^{it-1}$  and assumes the same reference trajectory and the same structure of the control law for both the actual and simulated robots. At step  $it$ , the simulated acceleration is given by

$$\hat{M}^{it-1} \ddot{q}_S^{it} = \tau_S^{it} - \hat{F}_v^{it-1} \dot{q}_S^{it} - \hat{F}_c^{it-1} \text{sign}\left(\dot{q}_S^{it}\right). \quad (18)$$

By integrating (18), the velocity  $\dot{q}_S^{it}$  and position  $q_S^{it}$  are obtained. The simulated force  $\tau_S^{it}$  is calculated as

$$\tau_S^{it} = g_r K_p K_v \left(q_r - q_S^{it}\right) - g_r K_v \dot{q}_S^{it}. \quad (19)$$

The instrumental variable matrix is the IDM built with the simulated data

$$Z_{idm}^{it} = X_{idm} \left(q_S^{it}, \dot{q}_S^{it}, \ddot{q}_S^{it}\right). \quad (20)$$

$y_{idm}$  and  $X_{idm}$  are built according to (9). At step  $it$ , the iterative IV estimates are given by

$$\hat{\theta}_{IV-idm}^{it} = \left(\left(Z_{idm}^{it}\right)^T X_{idm}\right)^{-1} \left(Z_{idm}^{it}\right)^T y_{idm}. \quad (21)$$

The covariance matrix of the IV estimates is calculated as explained in (Young 2011). This IV approach is interesting because it does not require the use of the tailor-made data prefiltering strategy and combines the direct and inverse dynamic models. Furthermore, this approach is able to identify 60 dynamic parameters of an industrial robot in 3 iterations as shown in (Janot *et al.* 2014).

### 4.2 IV identification for the DDM

Similarly, the DDM can be used as the auxiliary model and the instrumental matrix is the DDM built with the simulated data

$$Z_{ddm}^{it} = X_{ddm} \left(\tau_S^{it}, q_S^{it}, \dot{q}_S^{it}\right). \quad (22)$$

The iterative IV estimates are calculated as

$$\hat{\theta}_{IV-ddm}^{it} = \left(\left(Z_{ddm}^{it}\right)^T X_{ddm}\right)^{-1} \left(Z_{ddm}^{it}\right)^T y_{ddm}. \quad (23)$$

## 5. EXPERIMENTAL RESULTS

The EMPS is controlled in position with the PD control given in Section 2.5. Data are collected with a sampling frequency of 1kHz. The resolution of the encoder is 4 000 counts per revolution. The iterative IV-based methods are initialized as follows:  $\hat{M}^0 = 100Kg$ ,  $\hat{F}_v^0 = 0N/(m/s)$  and  $\hat{F}_c^0 = 0N$ . The value  $\hat{M}^0$  is a CAD value.

### 5.1 Appropriate data filtering

The cutoff frequency of the Butterworth filter is 60Hz while the cutoff frequency of the decimate filter is 40Hz. We keep one sample over 10. The cutoff frequencies are tuned according to the rules given in (Gautier *et al.* 2013).

The LS- and IV-based estimates obtained with the IDM are given in Table 1 while the LS- and IV-based estimates obtained with the DDM are given in Table 2. The IV method with the IDM and the DDM has converged in 3 iterations only (see the results given in Table 4 and Table 5). The identified values of the physical parameters are regrouped in the Table 3. In addition, the relative errors are given Table 1 and Table 2.

When using the IDM and the DDM, the LS estimates stick to the IV estimates. Furthermore, the small differences observed with the IV estimates are spanned by the IV deviations. According to the theory of Hausman (Hausman 1978), the LS estimates can be considered as unbiased. The results show that the values of the dynamic parameters can be retrieved with the values estimated with the DDM (see Table 3). However, their deviations cannot be easily calculated.

Direct measured and model output comparisons have been performed for the IV-IDM estimates, see Fig. 3 (a similar result is obtained for the DDM and similar results are obtained with the LS estimates for both the IDM and DDM). The estimated force matches the measured force. Since the relative errors are smaller than 10%, the identification results are of good quality.

If the data filtering is appropriate, the IV approach does not really improve the LS method. This is mainly due to the very accurate data and the data filtering. The matrices  $X_{idm}$  and  $X_{ddm}$  can be considered as noise-free and they are thus not correlated with the errors  $\mathcal{E}_{idm}$  and  $\mathcal{E}_{ddm}$ .

### 5.2 Inappropriate data filtering

The cutoff frequency of the Butterworth filter is 180Hz while the cutoff frequency of the decimate filter is 120Hz. We keep one sample over 3.

The LS and IV estimates obtained with the IDM are given in Table 6 while the LS and IV estimates obtained with the DDM are given in Table 7. The IV method with the IDM and the DDM has converged in 3 iterations only. The results are similar to those given in Table 4 and Table 5. The identified values of the physical parameters are shown in Table 8. In addition, the relative errors are given Table 6 and Table 7.

When an inappropriate data filtering is applied, the LS estimates of  $F_v$  and  $F_c$  stick to the IV estimates whereas the LS estimate of  $M$  does not. Furthermore, the difference with the IV estimate is not spanned by the IV deviation. According to the theory of Hausman, the LS estimate of  $M$  is biased. This outcome was expected and is due to the fact that the acceleration is the noisiest signal, which is correlated with the error because of the closed-loop control.

Direct comparisons have been performed. The result obtained with the IV estimates for the IDM is similar as the one illustrated Fig. 3 (a similar result is obtained for the DDM). The result obtained with the LS estimates for the IDM is illustrated in Fig. 4. With the IV method, the estimated force matches the measured force whereas it does not with the LS method. The reconstructed force is noisy because of the acceleration in (4). Furthermore, the relative errors are smaller than 10% with the IV method whereas they are close to 50% with the LS method. Such a relative error is a reason for alarm.

It comes that the IV approach really improves the LS method because of its robustness against noises in the observation matrix. It is worth noting that we obtain the same result with

a poor encoder resolution, smaller than 100 counts per revolution, associated with an appropriate data filtering.

Table 1. LS and IV estimates for the IDM model - Appropriate data filtering for LS method

Parameters	IDM-LS	% $\sigma_{\hat{\theta}_{idm_j}}$	IDM-IV	% $\sigma_{\hat{\theta}_{idm_j}}$
$M$	100.6	0.4%	100.2	0.5%
$F_v$	234.9	1.3%	236.9	1.5%
$F_c$	24.2	1.1%	24.8	1.2%
$\ \hat{\mathcal{E}}_{idm}\ /\ y_{idm}\ $	4.9%		5.2%	

Table 2. LS and IV estimates for the DDM model - Appropriate data filtering for LS method

Parameters	DDM-LS	% $\sigma_{\hat{\theta}_{ddm_j}}$	DDM-IV	% $\sigma_{\hat{\theta}_{ddm_j}}$
$\theta_1$	0.01	0.3%	0.01	0.3%
$\theta_2$	2.32	1.4%	2.35	1.5%
$\theta_3$	0.23	1.2%	0.23	1.3%
$\ \hat{\mathcal{E}}_{ddm}\ /\ y_{ddm}\ $	6.9%		6.9%	

Table 3. LS and IV estimates of the dynamic parameters for the DDM model - Appropriate data filtering for LS method

Parameters	DDM-LS	DDM-IV
$M$	100.0	100.0
$F_v$	232.0	235.0
$F_c$	23.0	23.0

Table 4. Convergence of the IV estimates for the IDM model

Parameters	0	1	2	3
$M$	100.0	100.0	100.2	100.2
$F_v$	0.0	236.0	236.9	236.9
$F_c$	0.0	23.9	24.8	24.8
$\ \hat{\mathcal{E}}_{idm}\ /\ y_{idm}\ $	24.4%	6.1%	5.2%	5.2%

Table 5. Convergence of the IV estimates for the DDM model - Appropriate data filtering for LS method

Parameters	0	1	2	3
$\theta_1$	0.01	0.01	0.01	0.01
$\theta_2$	0.0	2.33	2.35	2.35
$\theta_3$	0.0	0.22	0.23	0.23
$\ \hat{\mathcal{E}}_{ddm}\ /\ y_{ddm}\ $	21.7%	7.3%	6.9%	6.9%

Table 6. LS and IV estimates the for IDM model - Inappropriate data filtering for LS method

Parameters	IDM-LS	% $\sigma_{\hat{\theta}_{idm_j}}$	IDM-IV	% $\sigma_{\hat{\theta}_{idm_j}}$
$M$	54.9	1.0%	100.8	1.1%
$F_v$	236.9	3.7%	238.1	5.2%
$F_c$	23.5	3.4%	24.3	4.3%
$\ \hat{\mathcal{E}}_{idm}\ /\ y_{idm}\ $	48.7%		6.6%	

Table 7. LS and IV estimates for the DDM model - Inappropriate data filtering for LS method

Parameters	DDM-LS	% $\sigma_{\hat{\theta}_{ddm_j}}$	DDM-IV	% $\sigma_{\hat{\theta}_{ddm_j}}$
$\theta_1$	0.02	0.9%	0.01	1.0%
$\theta_2$	4.64	3.5%	2.31	4.1%
$\theta_3$	0.46	2.9%	0.24	3.6%
$\ \hat{\mathcal{E}}_{ddm}\ /\ y_{ddm}\ $	46.3%		8.1%	

Table 8. LS and IV estimates of the dynamic parameters for the DDM model - Inappropriate data filtering for LS method

Parameters	DDM-LS	DDM-IV
$M$	50.0	100.0
$F_v$	232.0	231.0
$F_c$	23.0	24.0

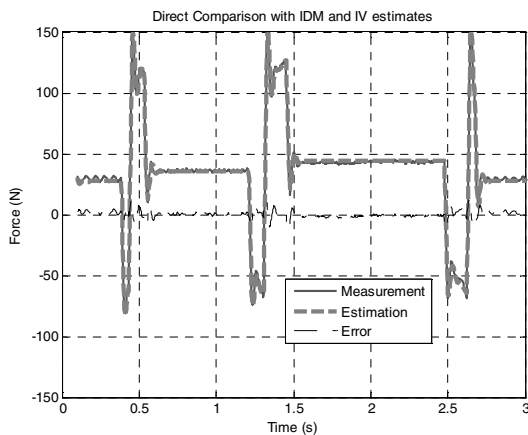


Fig. 3. Direct comparison with the IDM and IV estimates - zoom

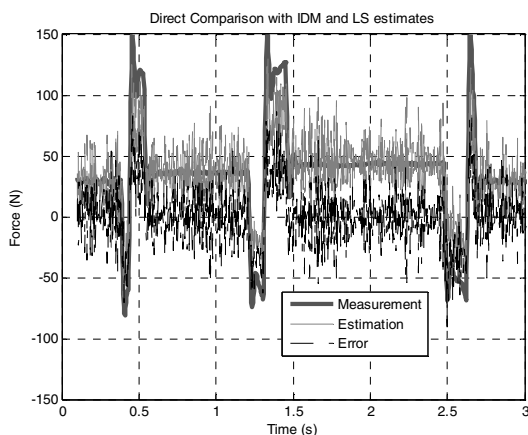


Fig. 4. Direct comparison with the IDM and LS estimates - Inappropriate data filtering - zoom

## 6. CONCLUSION

In this paper, the direct identification of the physical parameters of a one DOF electromechanical system that operates in closed loop was presented. Three identification methods were experimentally compared: the usual method which makes use of the inverse dynamic model and the LS method, an IV approach which makes use of the direct and inverse dynamic models and another IV approach which

makes use of the direct dynamic model only.

The experimental results show that the iterative IV method based on the use of the inverse and direct dynamic models seems to be more appropriate than the two others to identify the dynamic parameters. This method is robust against noises because a tailor-made data prefiltering is not required and the physical parameters are directly identified.

Future works concern the use of the IV method for flexible robot identification and the study of the robustness of IV method against low encoder resolution.

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