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An automated instrumental variable method for rigid industrial robot identification

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Abstract: Industrial robots must be operated in closed-loop since they are electro-mechanical systems with double integrator behaviour. Their mechanical model, called the Inverse Dynamic Identification Model (IDIM), is based on Newton's laws and has the advantage of being linear with respect to the parameters. The Instrumental Variable (IDIM-IV) method provides a robust solution to the closed-loop estimation problem. This method relies on a tailor-made prefiltering process in order to estimate accurate parameters. An alternative and automatic way of constructing the observation matrix has been recently introduced. If this methodology provides appropriate estimated parameters, it can fail to estimate the variances of those parameters. In this paper, an identification of the additive noise characteristics is included in the process to obtain correct and lower variances of the IDIM parameters. The evaluation of the new estimation algorithm on a one degree-of-freedom rigid robot shows that it improves statistical efficiency, while minimizing the a priori knowledge required from the practitioner.

Keywords: Robots identification; System identification; Instrumental Variable methods; Closed-loop identification; Robot dynamics

1. INTRODUCTION

During decades, Least-Squares (LS) optimization and estimation of the Inverse Dynamic Identification Model (IDIM) have been the two key elements of the most common method used for industrial robot identification: see e.g. (Gautier, 1997) or (Gautier et al., 2013). With the IDIM, the input torque is expressed as a linear function of the physical parameters: see e.g. (Khalil and Dombre, 2004). Nevertheless, it is not always robust to the measurement noise correlation that arises from the closed-loop structure required for robot operation. To overcome this issue, Instrumental Variable (IV) optimization has been suggested and adapted to robot systems in (Janot et al., 2014a).

The IDIM-LS and IDIM-IV methods, however, require the knowledge of the closed-loop system's bandwidths. A well-tuned bandpass filtering is indeed employed to generate the velocity and acceleration signals from the joint position measurements (Gautier, 1997). Furthermore, a *decimate* filter is also applied to remove high-frequency ripples and to provide white residuals. The setting of those filters may be an issue during early tests of the system, especially if the practitioner has no access to the key design parameters. Brunot et al. (2018b) have successfully employed a self-tuning method able to estimate the joint derivatives, which provides admissible physical parameters. Nonetheless, the residuals of the estimation cannot be considered as white due to the wrong setting of the *decimate* filter.

The assumption of whiteness is needed for the calculation of the variances.

In the field of automatic control, the IV-based methods have been studied to insure the consistency of the estimated parameters and to obtain optimal accuracy (Söderström and Stoica, 1983; Gilson et al., 2011). Amongst the different proposed solutions, an iterative algorithm, where the required prefilter comes from the identified noise model, is known to be one of the most reliable (Young, 2011).

The aim of this paper is, therefore, to deal with the *decimate* filter in an automated way. If ongoing work examines the replacement of the *decimate* filter, another perspective is chosen here: the filter is not replaced but completed by a noise filter identification. This noise identification compensates for the potential wrong setting of the *decimate* filter. The final goal is to provide estimated parameters with low and correct covariances, in an automated way. In this study, the identification procedure is evaluated and validated on a 1 Degree Of Freedom (DOF) robot for sake of clarity. This robot is the high-precision Electro-Mechanical Positioning System (EMPS) that only has 3 dynamic parameters, which makes the interpretation clear. More comprehensive work is ongoing to deal with a 6 DOF robot and without the *decimate* filter (Brunot et al., 2018a).

This paper is organised as follows. Section 2 describes the considered closed-loop system. The standard IDIM-LS and IDIM-IV methods are recalled in section 3. Section

4 is devoted to the introduced methodology. Then, this approach is evaluated using experimental data from the EMPS by considering two cases. First, we assume good a priori knowledge on the system, which allows a proper filtering; second, inadequate filtering is assumed due to a lack of knowledge about the robot characteristics. The conclusions are presented in section 6.

2. EMPS MODELLING AND CONTROL

2.1 EMPS Model

To evaluate the proposed methodology, the EMPS is considered; 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.

The Direct Dynamic Model (DDM) of a robot expresses the acceleration as a function of the motor torque, position and velocity (Khalil and Dombre, 2004). From Newton's law, we have

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

where M is the inertia of the arm; F_v and F_c are respectively the viscous and Coulomb frictions; q , \dot{q} and \ddot{q} are respectively the joint position, velocity and acceleration; τ_{idm} is the motor force.

The Inverse Dynamic Model (IDM) of a robot expresses τ as a function of q , \dot{q} and \ddot{q} . In the case of the EMPS, the IDM is given by

$$\tau_{idm}(t) = M\ddot{q}(t) + F_v\dot{q}(t) + F_c\text{sign}(\dot{q}(t)), \quad (2)$$

Equation (2) is linear in relation to the dynamic parameters,

$$\tau_{idm}(t) = [\ddot{q}(t) \quad \dot{q}(t) \quad \text{sign}(\dot{q}(t))] \boldsymbol{\theta} = \boldsymbol{\phi}(t)\boldsymbol{\theta} \quad (3)$$

where $\boldsymbol{\phi}(t)$ is the (1×3) observation matrix of basis functions of the IDM and $\boldsymbol{\theta} = [M \ F_v \ F_c]^T$ is the (3×1) vector of the 3 dynamic parameters. Because the DDM is usually nonlinear with respect to the dynamic parameters, it is rarely used (Swevers et al., 2007). In (Brunot et al., 2015), a comparison between the IDM and the DDM is made for the identification of the EMPS.

2.2 EMPS Control

The EMPS model (2) has a pure integrator and cannot therefore be identified in open-loop. The system is thus driven by a Proportional-Derivative (PD) controller. Gautier et al. (2013) have shown that a PD control is enough to identify the dynamic parameters of robots because an excellent tracking is not needed. The control signal ν is given by

$$\nu(t) = k_p k_v (q_r(t) - q(t)) - k_v \dot{q}(t), \quad (4)$$

where k_p is the proportional gain and k_v is the derivative gain. With the bandwidth of the position loop equal to 20

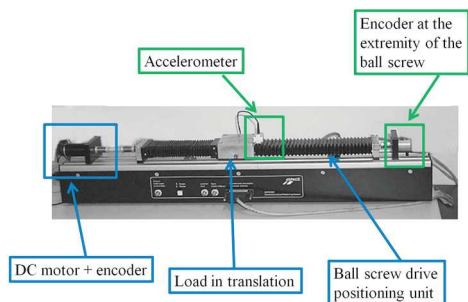


Fig. 1. EMPS prototype

Hz, the gains haven chosen such as $k_p = 160.18 \text{ 1/s}$ and $k_v = 243.45 \text{ V/m.s}^{-1}$. The control signal, coming from the control law, is linked to τ by the following relation

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

where g_τ is the drive gain of the EMPS. Although the drive gain is usually given by the manufacturer, it can be identified with special tests (Gautier and Briot, 2014). In this case, it has been estimated to $g_\tau = 35.15 \text{ N/V}$.

3. STANDARD METHODS FOR ROBOT IDENTIFICATION

3.1 Joint velocity and acceleration estimation

In most applications, the available information is the measurement of the joint position, q_m . The joint velocities and accelerations have to be calculated from this information in order to build the observation matrix $\boldsymbol{\phi}$ as described in (Gautier, 1997). q_m is firstly filtered to obtain \hat{q} . From this filtered position, the derivatives can be calculated with finite differences. The filter type and the cut-off frequency, ω_{f_q} , are selected such as $(\hat{q}, \hat{\dot{q}}, \hat{\ddot{q}}) \approx (q, \dot{q}, \ddot{q})$ in the range $[0, \omega_{f_q}]$. The filter, which is usually a Butterworth one, is applied in both forward and reverse directions to avoid lag introduction. The rule of thumb for the cut-off frequency is $\omega_{f_q} \geq 5\omega_{dyn}$, where ω_{dyn} is the natural frequency of the highest mode of the closed-loop system. The combination of the Butterworth filter and the central differentiation is referred to as the *bandpass* filtering process.

3.2 High-frequency ripples rejection

The IDIM differs from the IDM by an error term $v(t)$, resulting of perturbations coming from measurement noise and modelling errors. The IDIM is then given by:

$$\tau(t) = \tau_{idm}(t) + v(t) = \boldsymbol{\phi}(t)\boldsymbol{\theta} + v(t). \quad (6)$$

In practice, the torque is perturbed by high-frequency ripples which are rejected by the controller. Those ripples are removed with a parallel lowpass filtering of each basis function at the cut-off frequency $\omega_{F_p} \geq 2\omega_{dyn}$. The choice of ω_{F_p} is involved to keep enough information while avoiding the high frequency noise. Since there is no more useful information beyond the cut-off frequency, the data are also re-sampled by keeping one sample over n_d , i.e. n_d is the decimation factor. This combination of parallel filtering and re-sampling is referred to as the *decimate* process. After data acquisition and parallel filtering, we obtain

$$\begin{aligned}\tau_{F_p}(t) &= F_p(z^{-1})\tau(t) \\ &= \phi_{F_p} \left(\hat{q}(t), \hat{\dot{q}}(t), \hat{\ddot{q}}(t) \right) \boldsymbol{\theta} + v_{F_p}(t),\end{aligned}\quad (7)$$

where z^{-1} is the backward shift operator and F_p is the decimate filter applied to each element of the observation matrix, the torque signal and the error term.

3.3 The IDIM-LS and IDIM-IV methods

The IDIM-LS and IDIM-IV approaches exploit the IDIM model. In the IV case, for the EMPS, an (1×3) instrumental matrix, denoted by ζ , is introduced that must fulfil the following conditions:

- $\zeta^T \phi_{F_p}$ is full column rank,
- $\mathbb{E} [\zeta^T v_{F_p}] = 0$,

where $\mathbb{E}[\cdot]$ denotes the mathematical expectation. The first condition means that the instrumental matrix must be well correlated with the observations. The second condition expresses the fact that the instrumental matrix must be uncorrelated with the error. Assuming that the two previous conditions hold, it can be shown that the IV parameter estimates $\hat{\boldsymbol{\theta}}_{IV}(N)$ given by

$$\hat{\boldsymbol{\theta}}_{IV} = \left[\frac{1}{N} \sum_{i=1}^N \zeta^T(t_i) \phi_{F_p}(t_i) \right]^{-1} \left[\frac{1}{N} \sum_{i=1}^N \zeta^T(t_i) \tau_{F_p}(t_i) \right], \quad (8)$$

are asymptotically unbiased and consistent. In this IV solution, N is the number of sampling points considered for the identification. Note that the standard LS solution is obtained if ζ is replaced by ϕ_{F_p} but that, in general when there is noise on the data, the resulting estimates will be asymptotically biased and inconsistent.

During the last decade, different IV solutions have been developed for closed-loop identification; see e.g. (Gilson et al., 2011). One key feature of the IV method is the construction of the instruments; i.e. the elements of the instrumental matrix. There are a number of ways in which they can be constructed, see e.g. (Söderström and Stoica, 1983), but it has been found that by far the most successful of these is to generate the instruments using an *auxiliary model* of the system: see e.g. (Young, 2011) and the prior references therein. Janot et al. (2014b) have shown that the simulation of the whole robotic system using the DDM, including the inherent closed-loop, provides a very convenient auxiliary model. The simulation of this auxiliary model provides noise-free simulated signals that are used to construct the instrumental matrix using the same equations as those of the observation matrix. If the parameters of this auxiliary model are reasonable and there is no modelling error, the IV requirements will be satisfied and the resulting estimates will have the required properties. This is because the simulated signals are noise-free, since the only input to the simulation is the reference trajectory and this is known perfectly.

In order to ensure the efficacy of the parameters in the auxiliary model, the IDIM-IV method, like many IV-based methods of estimation, is an iterative process in which the estimates of the parameters from the previous iteration are used for the auxiliary model on the next iteration, as it is described in Figure 2. If the convergence cannot be

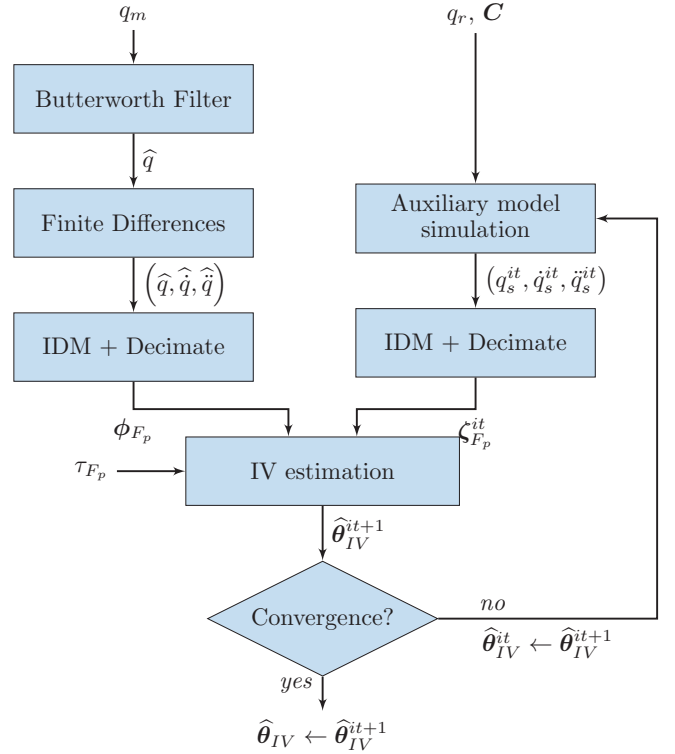


Fig. 2. Block diagram of the IDIM-IV methodology

guaranteed in this nonlinear situation, experience with the IDIM-IV algorithm shows that it is robust in this sense; see e.g. (Janot et al., 2014b; Brunot et al., 2015).

By noting the simulated signals with a subscript s , the instrumental matrix at iteration it is:

$$\zeta(t, \hat{\boldsymbol{\theta}}_{IV}^{it}) = F_p(z^{-1}) \phi \left(q_s(t, \hat{\boldsymbol{\theta}}_{IV}^{it}), \dot{q}_s(t, \hat{\boldsymbol{\theta}}_{IV}^{it}), \ddot{q}_s(t, \hat{\boldsymbol{\theta}}_{IV}^{it}) \right). \quad (9)$$

4. AN AUTOMATED IV FOR ROBOT IDENTIFICATION

As it has been seen in the previous section, the IDIM-LS and IDIM-IV methods rely on *a priori* knowledge and rules of thumb to tune the *bandpass* and *decimate* filters. Therefore, the practitioner must be skilled to employ those methods. An alternative and automatic methodology is thus presented here.

4.1 Joint derivatives with IRWSM

To estimate the joints velocities and accelerations without knowledge on the system bandwidth, a procedure, based on a Kalman Filter (KF) and a Fixed Interval Smoother (FIS), can be used. Applied to robot identification, the idea is to model the position with an Integrated Random Walk (IRW) such as

$$\begin{aligned}\begin{bmatrix} q(t_i) \\ \dot{q}(t_i) \end{bmatrix} &= \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} q(t_{i-1}) \\ \dot{q}(t_{i-1}) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \varpi(t_{i-1}), \\ q_m(t_i) &= q(t_i) + \xi(t_i),\end{aligned}\quad (10)$$

where ϖ and ξ are respectively the process and measurement noises; q and \dot{q} are the states that must be estimated with the combination of the KF and the FIS; Δt is the

fixed sampling period. The covariances of the noises are estimated thanks to a maximum likelihood optimisation. After estimation with the KF and the FIS, the estimated joint position, \hat{q} , and velocity, $\hat{\dot{q}}$, are available to construct the observation matrix. By applying the process twice, the joint acceleration is retrieved. It should be stressed that, thanks to maximum likelihood optimisation, the practitioner does not have to provide *a priori* knowledge to choose the covariances. Recently, (Janot et al., 2017) have introduced this alternative to the bandpass filtering process. In (Brunot et al., 2018b), it has been shown the relevance of this methodology to identify a 6 DOF industrial robot. The global process is referred to as the Integrated Random Walk SMOother (IRWSM) technique and is summarized in (Young, 2011). This IRWSM algorithm is coded as the routine `irwsm` in the CAPTAIN Toolbox¹ for MatlabTM.

4.2 Inverse noise filtering

The residual of estimation, at iteration $it + 1$, is given by

$$\epsilon_{\tau}^{it+1}(t) = \tau_{F_p}(t) - \phi_{F_p}(t)\hat{\theta}_{IV}^{it+1}. \quad (11)$$

If there is no modelling error, and, if $\hat{\theta}_{IV}^{it+1}$ is a consistent estimation of θ , this residual is a consistent estimation of the error v_{F_p} . The *decimate* filter, by removing high-frequency ripples, insures that v_{F_p} is a white noise sequence. This assumption is necessary for the calculation of the covariances of the estimated parameters. As observed in (Brunot et al., 2018b), if the IDIM-IV combined with the IRWSM can provide consistent estimated parameters, a wrong tuning of the *decimate* filter leads to a non-white residual.

According to the Refined IV theory (Young, 2011), there exists an optimal filter for the case where the additive noise is not purely white. This filter is said to be optimal because the resulting estimation reaches the Cramér-Rao lower bound (Kay, 1993), if there is no modelling error. For the system of linear equations (2), the optimal filter would be $H_{\tau}^{-1}(z^{-1})$, with H_{τ} given by:

$$v(t) = H_{\tau}(z^{-1})e(t), \quad (12)$$

where e is a Gaussian white noise. Nonetheless, the property of optimality is valid only for Linear Time Invariant (LTI) systems. In this article, the goal is not to develop a theory of the optimality for the nonlinear systems that are the robots. That would be indeed far beyond the scope of this article, which only aims to adapt such a technique.

A first idea could be to replace the *decimate* filter by the identification of H_{τ} . Nonetheless, it may be feared that the resulting model could be large, due to the large sampling frequency, and complex, due to high-frequency ripples and potential modelling errors. We therefore suggest to model the noise such as:

$$v_{F_p}(t) = H'_{\tau}(z^{-1})e'(t). \quad (13)$$

where e' is a white noise, with zero mean and covariance λ ; H'_{τ} is a discrete-time transfer function, which is assumed to be asymptotically stable and invertible.

The idea is to keep the *decimate* filter, even if it is badly tuned, and to model the remaining error. This

¹ This Toolbox is available free and can be downloaded via <http://captaintoolbox.co.uk>.

may save computation time while still preventing the estimation from high frequency ripples. The counterpart is the lost of the physical meaning of the noise model. A characterisation of the sensors' dynamics indeed makes no sense at the decimation frequency. The practitioner should in any case be cautious with the inverse noise filtering; it must not cancel the effect of the *decimate* filter.

4.3 Noise identification

In general terms, H'_{τ} is represented by an AutoRegressive, Moving Average (ARMA) model, under the assumption that the noise has rational spectral density. However, an easier alternative is used here: an AutoRegressive (AR) model. Its order is found by linear search by using the Akaike Information Criterion (AIC); as implemented by the `aic` routine in CAPTAIN.

The separation of the identification of the dynamic model and the one of the noise assumes that both models are statistically independent. The practitioner must therefore be cautious and be confident about the dynamic model, before starting the noise identification. Otherwise, the noise model could encompass unmodelled physical dynamics and not only measurement noise introduced by the sensors.

4.4 The IDIM-AIV methodology

The IDIM-IV methodology is revised to include the IRWSM approach and the noise filter identification. Figure 3 describes the resulting methodology, where C is the control law. From the residual, ϵ_{τ}^{it+1} , the noise filter is identified with the `aic` routine. The subscript f designates the signals which have been filtered by the *decimate* filter and the inverse noise model. This new methodology is referred to as the Automated IV (IDIM-AIV) due to this specific prefiltering process.

This simple method of noise model identification, combined with the `irwsm` approach to signal differentiation, means that IDIM-AIV algorithm does not require any access to prior information and so it is easier to apply in practice. In fact, a cut-off frequency is required for the *decimate* filter. However, as shown in section 5, this knowledge is no longer critical.

5. EXPERIMENTAL RESULTS

The EMPS is controlled in position with the PD control given in section 2. Data are collected over a 24 s test, with a sampling frequency of 1 kHz. The resolution of the encoder is 4 000 counts per revolution. The iterative IV-based methods are initialized as follows: $\widehat{M}^0 = 100$ kg, $\widehat{F}_v^0 = 0$ N/(m/s) and $\widehat{F}_c^0 = 0$ N. The value \widehat{M}^0 comes from CAD values. The maximum size of the AR filters is arbitrary set to 10 in order to avoid a too heavy computation. The system is excited with a signal based on a trapeze velocity profile; see Chapter 4 of (Siciliano et al., 2009).

5.1 Good a priori knowledge

For the usual methods, the cutoff frequency of the Butterworth filter is 60 Hz while the cutoff frequency of the *decimate* filter is 40 Hz. We keep one sample over 10. Those

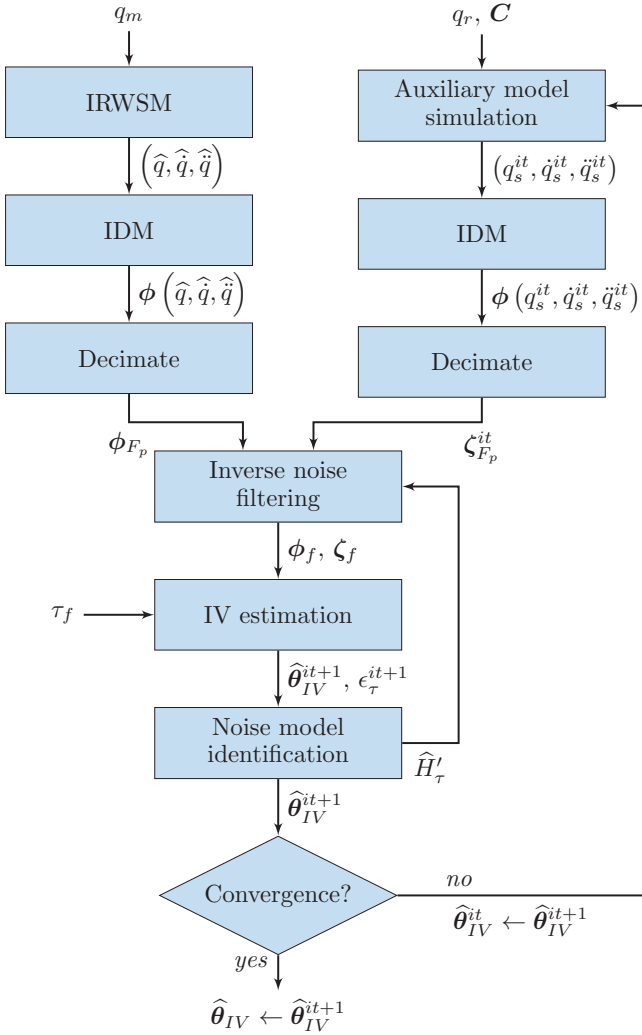


Fig. 3. Block diagram of the IDIM-AIV methodology

cutoff frequencies are tuned according to the rules given in sections 3.1, 3.2 and the references given therein.

The IDIM-LS, IDIM-IV and IDIM-AIV estimates are given in Table 1. Since the data filtering is appropriate, the IV methods do not really improve the IDIM-LS one. This is mainly due to the very accurate data and the data filtering. The observation matrix can be considered as noise-free and it is thus not correlated with the noise. This analysis explains why the LS estimates match the IV estimates. With respect to the estimation of the joint velocity and acceleration, as shown in (Brunot et al., 2018b), the IRWSM approach provides as good results as an usual Butterworth filter correctly tuned.

Regarding the relative standard deviations, they are slightly lower with the IDIM-AIV method. That confirms the contribution of this method. There is a slight discrepancy with regard to the viscous friction coefficient. However, this has already been observed in previous work (Brunot et al., 2016) and can be linked to the asymmetry of the friction model (Janot et al., 2017).

To complete the study of the standard deviations, Figure 4 illustrates the estimated autocorrelations of the residuals, where the blue lines show the 2σ confidence interval.

Table 1. Identified parameters and relative standard deviations – Good *a priori* knowledge

	IDIM-LS	IDIM-IV	IDIM-AIV
M	94.54 (0.34%)	94.53 (0.34%)	94.98 (0.18%)
F_v	200.9 (1.37%)	200.9 (1.38%)	210.8 (1.19%)
F_c	20.66 (1.18%)	20.66 (1.19%)	19.89 (1.12%)

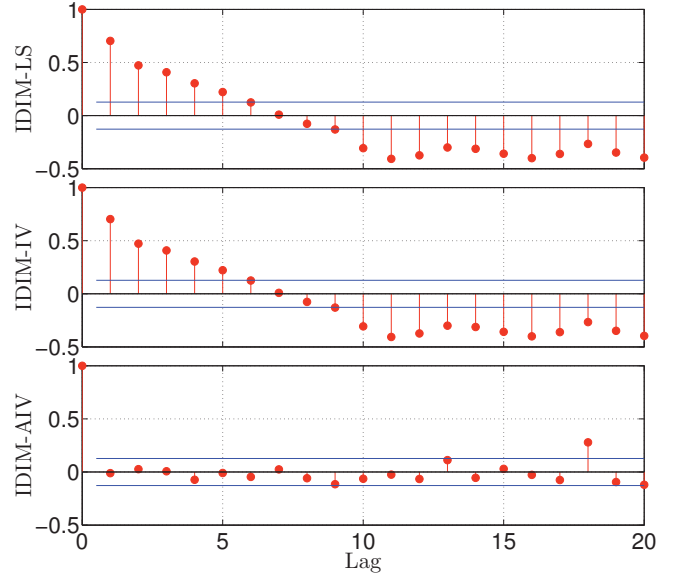


Fig. 4. Residuals autocorrelations – Good *a priori* knowledge

To validate the white noise assumption used for the computation of the standard deviations, the residuals should be serially decorrelated; i.e. all the coefficients should be within the blue lines, for non zero lags. That is therefore not perfect for the IDIM-LS and IDIM-IV methods, whereas it can be considered as satisfactory for the IDIM-AIV one. This illustrates the role of the noise filtering that whitens the residuals.

5.2 Poor *a priori* knowledge

To deal with the case where the robot is still unknown, larger cutoff frequencies are selected. This is likely the case with preliminary identification tests. In accordance with (Brunot et al., 2015), the cutoff frequency of the Butterworth filter is 180 Hz while the cutoff frequency of the decimate filter is 120 Hz.

The IDIM-LS, IDIM-IV and IDIM-AIV estimates are given in Table 2. For the IDIM-IV and IDIM-AIV methods, the results are similar to those given in Table 1. The estimated mass of the IDIM-LS method is reason for alarm. That is due to the presence of noise in the observation matrix because of the inappropriate filtering. Such a discrepancy in the inertia reflects a wrong estimation of the system's bandwidth. This observation is consistent with previous work (Brunot et al., 2015).

The advantage of the IDIM-AIV method compared with the IDIM-IV one appears with the relative standard deviations and by looking at Figure 5. The former are indeed

Table 2. Identified parameters and relative standard deviations – Poor *a priori* knowledge

	IDIM-LS	IDIM-IV	IDIM-AIV
M	74.69 (0.89%)	95.38 (0.89%)	95.99 (0.22%)
F_v	201.5 (4.08%)	190.6 (4.76%)	191.7 (1.58%)
F_c	20.60 (3.56%)	21.68 (3.71%)	21.39 (1.25%)

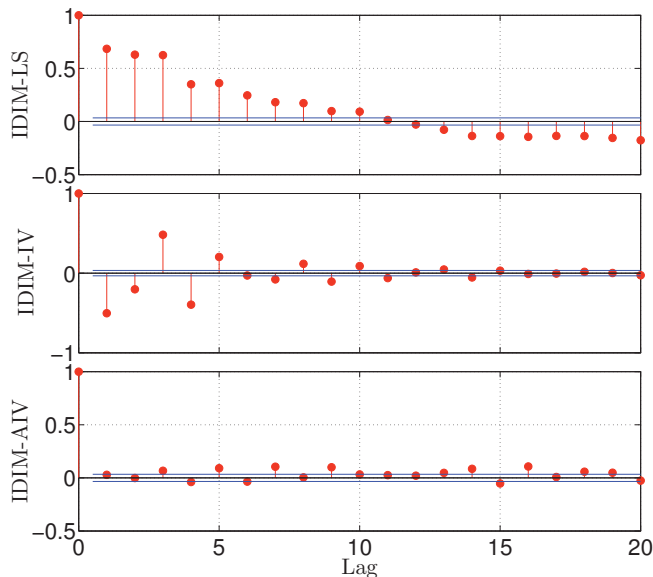


Fig. 5. Residuals autocorrelations – Poor *a priori* knowledge

lower for the IDIM-AIV estimates and the latter depicts whiter residuals for the IDIM-AIV method. The confidence intervals (blue lines) are narrower than in the good *a priori* knowledge case since there are more sampling points to consider due to the larger decimation frequency. It is worth noting here that the maximum order for the linear search of the *aic* routine is still 10. A larger one could be considered but at the expense of a larger computational load.

6. CONCLUSION

In this paper, the identification of electromechanical systems that operate in closed-loop was revisited with an Automated Instrumental Variable method. The idea is to enhance the usual IDIM-IV method with an identification of the remaining noise. The aim is to provide estimated parameters with lower and reliable variances.

The experimental results show that the prefiltered IV method based on the use of the inverse dynamic identification model 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. In addition, the method gives lower estimated covariances.

Future works concern the use of the IV method for flexible robot identification and the study of recursive IV methods for online estimation.

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