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Design and Tuning of Extended Kalman Filter for Robotic System Identification

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Abstract—Traditional identification approaches for robotic systems based on the inverse dynamic model and the least-squares method are the most used to identify dynamic parameters of robots. However these methods often require a well-tuned filtering or estimation of the position, velocity, acceleration and torque to avoid bias in identification results. The cutoff frequency of the low-pass filter that is usually used must be well chosen, which is not always a trivial task. In this paper, we propose to use an extended Kalman filter to reduce the noise on the measured position and to estimate the velocity and acceleration. These estimates can then be fed to the controller to further reduce the noise in the control torque.

The effect of the tuning of this filter is examined and the presented approach is validated through simulations and experiments on a one degree of freedom system.

I. INTRODUCTION

Many applications in robotics, such as torque control of industrial robots [1], [2] or impedance control in human-robot interaction applications like rehabilitation [3], require an accurate and a good knowledge of the dynamic model parameters of the robot.

Least squares (LS) are widely used in the context of rigid robotics to identify inertial and friction parameters of many robots. Gautier *et al.* [4] demonstrated that if a well-tuned filtering of the observation matrix and the measured torque is employed with LS, good identification results can be achieved with low computational cost. However, quantized position measurements using sensors with large quantization steps can lead to noisy derivative estimations and induce an ill-conditioned observation matrix. Furthermore, noisy control torques arise from the use of these signals as input to the PID controller used in robotic systems. Because of noisy measurements and incorrect data filtering, LS estimates may become extremely biased, to the point of losing all physical consistency.

Other methods robust to noisy position measures have been proposed in the literature such as the direct and inverse dynamic identification method (DIDIM) [5]. Although DIDIM requires greater computational effort, it gives good identification results. However, low-pass filtering of the measured torque signal is still required and the cutoff frequency f_c of this filter must be well chosen. In [4] and [6] f_c was chosen according to an a priori knowledge of the robot dynamic frequency, which is not necessarily an accessible value and is not always well defined for non-linear systems.

Alternative methods can be used, such as for example those based on Kalman filtering. In [7] identification results using the weighted least squares (WLS) estimation and using the extended Kalman filtering (EKF) joint method were compared. It was concluded that the EKF does not improve results over the WLS method aside from having a slower convergence speed. This unwanted time consumption may be caused by the use of the EKF joint method, in which state and parameters are estimated simultaneously within a single Kalman filter and are recursively updated at each time step. Meanwhile, a technique for estimating the dynamic parameters of a manipulator and its load using a dual EKF method has been introduced in [8]. The system state and parameters are identified separately within two concurrent Kalman filter instances. A disadvantage of this method is that it assumes that position, velocity, and acceleration are known, whereas robotics encoders typically only provide position.

To limit the influence of quantization on identification results, an EKF has been proposed in a preliminary version of this work [9] to estimate the position and velocity of the system based on the quantized position measurements. The tuning of this filter is simplified and is based on known sensor characteristics and on a user-defined estimation of the confidence on the initial model parameter estimations. A first identification method applying the LS technique used the position and velocity estimates to construct the observation matrix. A second method further employed these estimates as inputs to the PID controller to reduce the noise in the control torque and then use this torque in the LS technique. A last method used only this estimated torque signal with the DIDIM approach. This paper contains detailed examination of the effect of the tuning of the EKF as well as a comparison of the suggested methods with LS and DIDIM in simulation and experimental validation with a one degree of freedom robotic system.

This paper is organized as follows: existing and proposed identification methods for robotic systems are recalled in section II. Section III shows simulation results and discussions for the validation of the proposed methods. Then, section IV presents experimental results and discussion. Finally, section V includes the conclusion and future works.

II. IDENTIFICATION METHODS

A. Background

1) *Identification Model:* The inverse dynamic model (IDM) of a rigid robot with n degrees of freedom (DOF) calculates the joint forces and torques $\tau \in \mathbb{R}^n$ as a function of joint positions, velocities and accelerations $q, \dot{q}, \ddot{q} \in \mathbb{R}^n$. It can be obtained from the Newton-Euler or the Lagrangian equations [10] as follows:

$$\tau = M(q) \cdot \ddot{q} + C(q, \dot{q}) \cdot \dot{q} + g(q) + f(\dot{q}), \quad (1)$$

where $M(q) \in \mathbb{R}^{n \times n}$ is the robot inertia matrix, $C(q, \dot{q}) \in \mathbb{R}^{n \times n}$ is the Coriolis and centrifugal matrix, $g(q) \in \mathbb{R}^n$ is the gravitational term, and $f \in \mathbb{R}^n$ is the friction term. Several friction models exist [11]. A widely used one is given by the following:

$$f_j = F_{v_j} \cdot \dot{q}_j + F_{c_j} \cdot \text{sign}(\dot{q}_j), \quad (2)$$

with F_{v_j} and F_{c_j} the viscous and Coulomb's friction coefficients of the j th joint, respectively. The IDM in (1) can be expressed as a linear function of the standard dynamic parameters $\chi = [\chi_1^T \chi_2^T \cdots \chi_n^T]^T \in \mathbb{R}^p$ as follows:

$$\tau = IDM_\chi(q, \dot{q}, \ddot{q})\chi, \quad (3)$$

where $IDM_\chi(\ddot{q}, \dot{q}, q) \in \mathbb{R}^{n \times p}$ is the model regressor and χ_j contains inertia parameters, first moment and mass, as well as the inertia of the actuator and the friction parameters of the j th link.

The IDM (3) can be further reduced to only depend on the minimal set of base inertial parameters $\beta \in \mathbb{R}^b$ [12], also known as identifiable parameters [13], such that the measured torque τ_m can be represented as follows:

$$\tau_m = IDM_\beta(q, \dot{q}, \ddot{q})\beta + e, \quad (4)$$

where $IDM_\beta(q, \dot{q}, \ddot{q}) \in \mathbb{R}^{n \times b}$ is the reduced model regressor and $e \in \mathbb{R}^n$ is the error due to measurement noises and modeling uncertainties present in practice.

When the robot is controlled to follow an exciting trajectory of N samples with sampling time T_s , optimized so that the observation matrix W is well-conditioned [1], an overdetermined linear system with $r = n \cdot N$ equations and b unknowns is obtained, such that

$$Y = W(q, \dot{q}, \ddot{q})\beta + \epsilon, \quad (5)$$

where $Y \in \mathbb{R}^r$ is the sampled vector of τ_m ; $W(q, \dot{q}, \ddot{q}) \in \mathbb{R}^{r \times b}$ is the sampled matrix of $IDM_\beta(q, \dot{q}, \ddot{q})$, referred to as the observation matrix; and $\epsilon \in \mathbb{R}^r$ is the sampled vector of errors e .

2) *Least Squares:* Ordinary least squares (OLS) is a non-iterative widely used method to identify robot base inertial parameters β using measured joint torques and positions as illustrated in Fig. 1. OLS solution $\hat{\beta}$ consists in minimizing the 2-norm of the error vector ϵ as follows:

$$\hat{\beta} = \min_{\beta} \|\epsilon\|^2. \quad (6)$$

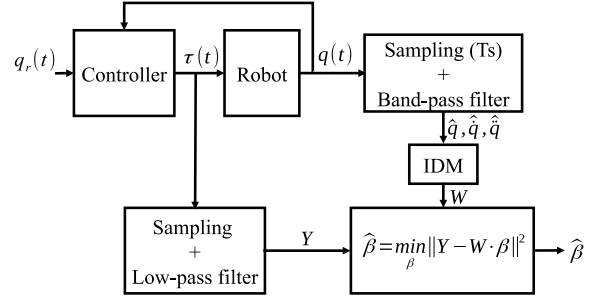


Fig. 1: Least squares identification scheme of robot's base inertial parameters β considering noisy torque measurements Y and an observation matrix W computed using the inverse dynamic model (IDM) with quantized position measurements q and its derivatives of velocity \dot{q} and acceleration \ddot{q} .

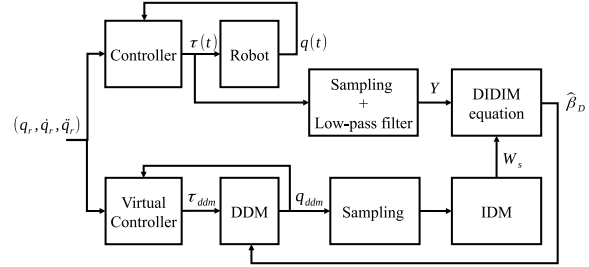


Fig. 2: Direct and inverse dynamic identification method (DIDIM) scheme for identification of β considering noisy torque measurements Y and an observation matrix W_s computed using the inverse dynamic model (IDM) with position q_{ddm} , velocity \dot{q}_{ddm} and acceleration \ddot{q}_{ddm} computed using the direct dynamic model (DDM) of the robot.

Solving (5) using OLS results in the following estimate

$$\hat{\beta} = (W^T W)^{-1} W^T Y. \quad (7)$$

One issue with the least square methods' parameter estimations is their vulnerability to measurement noise affecting the observation matrix. To overcome this limitation, one option is to use data filtering [4], while another is to employ identification methods that are robust to violation of this condition such as the one presented in the following.

3) *Direct and Inverse Dynamic Identification Method:* The direct and inverse dynamic identification method (DIDIM) [5] consists in using simultaneously the inverse dynamic model and the direct dynamic model (DDM). As illustrated in Fig. 2, the DIDIM uses only the measured torque while the observation matrix is constructed from the position and its derivatives simulated using the ideal DDM. At iteration k , the DIDIM estimate $\hat{\beta}_D^k$ can be identified using the following equation

$$\hat{\beta}_D^k = (W_s^{kT} W_s^k)^{-1} W_s^{kT} Y, \quad (8)$$

where $W_s^k \in \mathbb{R}^{r \times b}$ is the observation matrix at iteration k constructed using the noise-free simulated positions, velocities and accelerations.

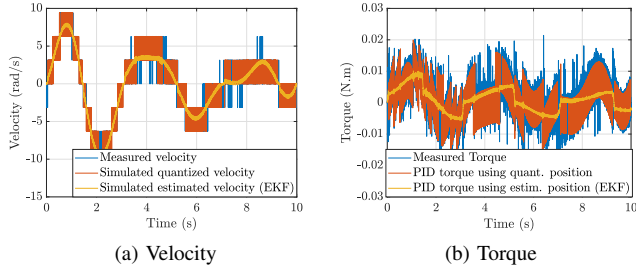


Fig. 3: Comparison between different a) velocity and b) torque signals: real measured signals (blue), signals computed from a simulated quantized system (orange) and signals computed using the simulated output of the proposed EKF tuned with 30% uncertainty on the parameters (yellow).

4) *Data Filtering*: To produce acceptable identification results, due to quantification noise in position q and the noise resulting from the differentiation of this position to calculate the velocity \dot{q} (see Fig. 3a) and acceleration \ddot{q} , filtering is required when using the LS approach. Without filtering, estimates may become biased and possibly lose their physical consistency. This is less critical with the DIDIM technique since only the measured control torque is used. Nonetheless, filtering is still required to eliminate torque noise (see Fig. 3b) caused by the quantized signals used as the PID controller's input.

A low-pass filter is often used for filtering [4], [14]. In both LS and DIDIM identification approaches, a well-tuned cutoff frequency f_c is required. In [4] and [5], $f_c > 10 w_{dyn}$ is chosen, where w_{dyn} is the system natural frequency. This value is not always known in practice and is not always easy to define for nonlinear systems. Coulomb friction may introduce high frequencies in the system while the frequency spectrum of quantization noise is often unknown. It is thus unclear whether or not low-pass filtering is sufficient to properly remove the noise while keeping the system dynamics, so that alternative processing methods can be used instead.

B. Proposed Method

1) *Extended Kalman Filter*: We propose using an extended Kalman filter, commonly employed for state estimation, to improve identification results. We consider here the state $x = [q^T \dot{q}^T]^T \in \mathbb{R}^{2 \cdot n}$. The state space model can then be obtained using the DDM as

$$\begin{aligned} \dot{x} &= \begin{bmatrix} \dot{q} \\ \ddot{q} \end{bmatrix} = \begin{bmatrix} \dot{q} \\ DDM_{\beta}(q, \dot{q}, \tau) \end{bmatrix}, \\ &= \begin{bmatrix} \dot{q} \\ M(q)^{-1} (\tau - C(q, \dot{q})\dot{q} - g(q) - f(\dot{q})) \end{bmatrix}. \end{aligned} \quad (9)$$

The discretization of (9) leads to the state transition equation:

$$x_{k+1} = x_k + \dot{x}_k(x_k, \tau_k, w_k, \beta) \cdot T_s, \quad (10)$$

with T_s the sampling time and $w_k \sim \mathcal{N}(0_{b \times 1}, Q)$ a non-additive process noise with diagonal covariance matrix

$$Q = \text{diag} \left(\begin{bmatrix} \sigma_{w_{k,1}}^2 & \sigma_{w_{k,2}}^2 & \cdots & \sigma_{w_{k,b}}^2 \end{bmatrix} \right), \quad (11)$$

where $\sigma_{w_{k,i}}^2$ is the variance of $w_{k,i}$, $i = 1, \dots, b$.

This noise affects the dynamic parameters of the system such that each parameter β_i in the DDM is replaced in (10) by a noisy version $\hat{\beta}_i$ of the initial estimate β_i^{EKF} defined as

$$\hat{\beta}_i = (1 + w_i) \cdot \beta_i^{EKF}. \quad (12)$$

The observation equation is given by:

$$y_k = q_k = [I_n \ 0_n] \cdot x_k + v_k, \quad (13)$$

where $v_k \sim \mathcal{N}(0_{n \times 1}, R)$ is an additive measurement noise, with $R \in \mathbb{R}^{n \times n}$ its covariance matrix.

EKF Tuning: One issue with the extended Kalman filter is that the matrices R and Q must usually be fine-tuned to obtain good filtering properties. The benefit of the chosen formulation is how easily these matrices may be set.

Assuming that the quantization error is the major source of noise in position measurements and under the assumption that it can be modeled as a white uniform noise, its covariance matrix is known to be as follows [15]:

$$R = \text{diag} \left(\begin{bmatrix} \sigma_{v_1}^2 & \sigma_{v_2}^2 & \cdots & \sigma_{v_n}^2 \end{bmatrix} \right), \text{ with } \sigma_{v_j}^2 = \frac{(\delta_{quant}^j)^2}{12}, \quad (14)$$

with δ_{quant}^j the known quantization step of the j th encoder.

Q can be set from an approximate guess on the percentage of uncertainty on β^{EKF} set in the EKF by the user. The influence of this parameter is studied in section III-B.

2) *Identification Using Extended Kalman Filter*: To mitigate the impact of noise on the identification results when using the least squares method, we first propose to compute the observation matrix W in (5) using $(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}})$, where \hat{q} and $\dot{\hat{q}}$ are estimated from the previously described EKF, while $\ddot{\hat{q}}$ is computed as a central difference derivative of $\dot{\hat{q}}$. The estimation process and control structure are illustrated in Fig. 4 using the green dashed line (---). This method has the benefit of not modifying the structure of the controller. However, the PID control torque signal Y still remains noisy due to the usage of the measured quantized position as the controller input. An alternative is to modify the control structure by using the estimates $(\hat{q}, \dot{\hat{q}})$ as the controller inputs as shown in Fig. 4 using the red dash-dotted line (-.-). In such a case, identification results using LS and DIDIM techniques are expected to be improved.

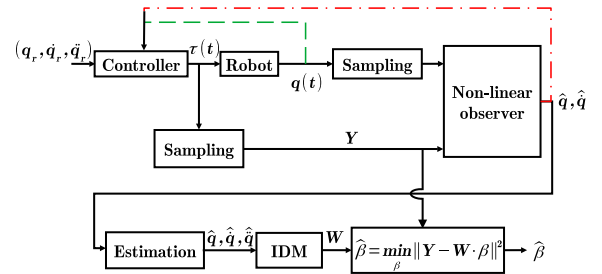


Fig. 4: Two least squares identification methods of parameters β from torque measurements Y : standard control structure using quantized position (---) or modified control structure using position \hat{q} and velocity $\dot{\hat{q}}$ estimated from the EKF (-.-). W is computed using \hat{q} and $\dot{\hat{q}}$ in the IDM.

III. SIMULATION

To validate the proposed identification technique, a model of the 1 DOF real system illustrated in Fig. 7 was implemented for simulation in Matlab/Simulink as it provides the ground-truth values β of the model parameters.

In such a case, the IDM in (1) may be reduced to:

$$\tau = J \ddot{q} + F_v \dot{q} + F_c \text{sign}(\dot{q}) + M_s g \cos\left(\frac{q}{N} + \theta_0\right), \quad (15)$$

where N is the reduction ratio, g is the gravitational acceleration, θ_0 is the angular offset of the handle from the horizontal position, M_s is the first moment, J is the equivalent inertia of the motor shaft and the handle, F_v and F_c are the friction coefficients defined in (2).

The state transition equation (10) then becomes:

$$x_{k+1} = \begin{bmatrix} q_k \\ \dot{q}_k \end{bmatrix} + \left[\frac{1}{J} \left(\tau_k - \hat{F}_v \dot{q}_k - \hat{F}_c \text{sign}(\dot{q}_k) - \hat{M}_s g \cos\left(\frac{q_k}{N} + \theta_0\right) \right) \right] \cdot T_s, \quad (16)$$

with $\hat{M}_s = (1 + w_1)\hat{M}_s^{EKF}$, $\hat{J} = (1 + w_2)\hat{J}^{EKF}$, $\hat{F}_v = (1 + w_3)\hat{F}_v^{EKF}$ and $\hat{F}_c = (1 + w_4)\hat{F}_c^{EKF}$, where \hat{M}_s^{EKF} , \hat{J}^{EKF} , \hat{F}_v^{EKF} and \hat{F}_c^{EKF} are the initial estimations of, respectively, M_s , J , F_v and F_c in the EKF.

A. Simulation Setup

We compare different identification methods in order to evaluate the efficiency of our approach:

Method 1: LS with quantized data (see Fig. 1).

Method 2: DIDIM with quantized data (see Fig. 2).

Method 3: LS with measured torque but position and velocity estimated using the proposed EKF (see green dashed line in Fig. 4 - - -).

Method 4: LS with torque computed from the position and velocity estimated using the proposed EKF (see red dash-dotted line in Fig. 4 - · - ·).

Method 5: DIDIM with torque computed from the position and velocity estimated using the EKF.

To study the influence of an inaccurate estimation of the parameters $\hat{\beta}^{EKF}$ in the EKF, we also compare five cases: $\hat{\beta}^{EKF} = 0.3 \cdot \beta$, $\hat{\beta}^{EKF} = 0.7 \cdot \beta$, $\hat{\beta}^{EKF} = \beta$, $\hat{\beta}^{EKF} = 1.3 \cdot \beta$ and $\hat{\beta}^{EKF} = 2 \cdot \beta$. The nominal measurement noise covariance is set to $R_0 = (0.0031416)^2/12 = 8.2247 \cdot 10^{-7} \text{rad}^2$ based on (14) and the quantization step of the real system. The initial value of the state is set to $x_0 = [0 \ 0]^T$ to fit the excitation trajectory and its covariance matrix is set to a diagonal matrix $P_0 = \text{diag}([R_0 \ 0.1])$.

B. Effect of Noise Covariance Matrices on the Identification

To study the effect of the tuning of R and Q on the identification results, a variation of R is considered around the nominal value R_0 in the interval $[R_0 \times 10^{-3}, R_0 \times 10^3]$. Similarly we set $Q = \sigma_w^2 \cdot I_4$, i.e. with the same relative uncertainty on all parameters, and taking $\sigma_w^2 \in [10^{-8}, 10^8]$.

An example of identification of the first moment M_s using Methods 1 and 3 is shown in Fig. 5. It can be seen that

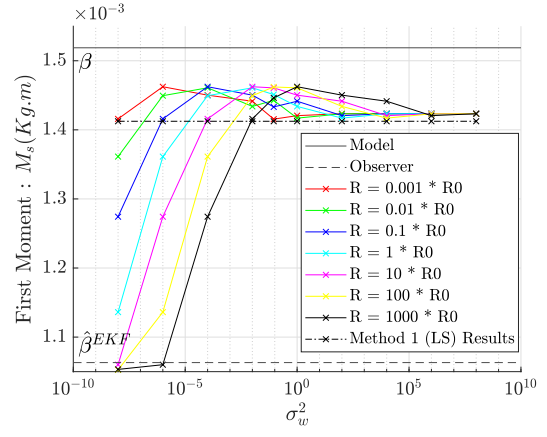


Fig. 5: Comparison of identification results of M_s using Method 3 with different values for R and Q (σ_w^2).

the curves drawn for a constant value of R tends to have a similar shape and are only shifted to the right as R increases. Hence the identification results seem to only depend on the ratio between R and σ_w^2 . Consequently, in the followings R is set to its nominal value R_0 and only σ_w^2 is modified.

C. Simulation Results and Discussion

Fig. 6 compares the identified parameters obtained using Methods 1 to 5 to the ground-truth values and the values set in the EKF. Looking at Methods 3 and 4, it can be seen that for large values of σ_w^2 , i.e. low confidence in the model parameters, the identified values tend to converge towards wrong values. This could be expected since the EKF would follow the measures and provide almost no filtering in this case. On the other side, for small values of σ_w^2 , i.e. high confidence in the model parameters, the identified values tend to converge towards the values set in the EKF. This could also be expected since the EKF would then stay close to the model behavior even if its output deviates from the measures, leading to an incorrect computation of the observation matrix. Therefore, our range of interest for the analysis of the results will be for $\sigma_w^2 \in [10^{-4}, 1]$.

In this range both Methods 3 and 4 provide identification of the friction parameters closer to the ground-truth compared to Method 1 (see Fig. 6d, 6e, 6g and 6h), which can be explained by the good estimation of the velocity (see Fig. 3a). Method 4 is also slightly more consistent in this range than Method 3, which could be explained by the additional filtering of the torque signal (see Fig. 3b). Identification of the inertia with Methods 3 and 4 can give better results than Method 1 in some cases (see Fig. 6a and 6b), however it seems quite sensitive to the good tuning of both σ_w^2 and $\hat{\beta}^{EKF}$ in the EKF, which is not practical.

Concerning the DIDIM approach, it can be seen on Fig. 6c, 6f and 6i that the identified values are close to the ground-truth for both Methods 2 and 5 for high and low values of σ_w^2 . However, in the smaller range of interest, Method 5 seems more sensitive to the tuning of σ_w^2 when $\hat{\beta}^{EKF}$ is overestimated in the EKF (see light blue and pink lines). On the contrary, when $\hat{\beta}^{EKF}$ is close to the real values or slightly underestimated (see dark blue and green lines)

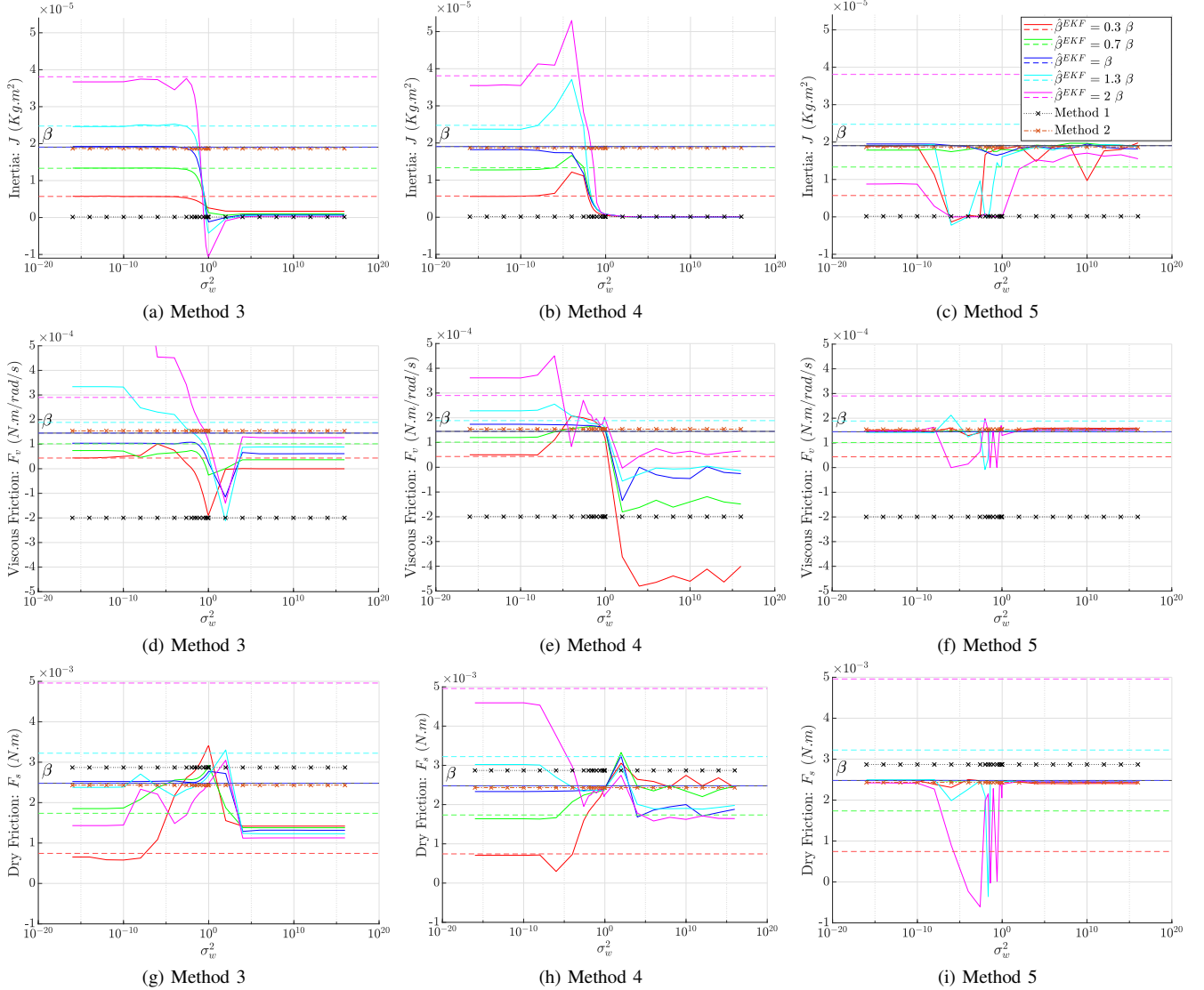


Fig. 6: Identification results $\hat{\beta}$ (solid lines) of the dynamic parameters β using Methods 1 to 5 with $R = R_0$, varying values of Q and different estimated values $\hat{\beta}^{EKF}$ (dashed lines) of the parameters set in the EKF.

Method 5 is almost independent of the tuning of σ_w^2 like is the case in Method 2. In addition, we observed that adding the EKF doesn't affect the fast convergence of the DIDIM. Hence, the addition of the EKF seems to be adequate to improve the LS identification results and Method 5 provides the added benefit of not requiring a fine tuning of this EKF.

IV. EXPERIMENTAL VALIDATION

A. Experimental Setup

The actual system depicted in Fig. 7 is a cable-driven robot joint. It is made up of a handle and a mass linked by a cable (reduction ratio 15) to a Maxon motor (EC-max 40mm, brushless 120W, model 283871) with a HEDL 5540 encoder that measures the angular position of the motor shaft with a resolution of 500 counts per turn corresponding to a quantization step $\delta_{quant} = 2\pi/(500 \times 4) = 0.0031416 \text{ rad}$. The PID controller and EKF are implemented in an EPOS3

driver (Maxon) running via TwinCAT (Beckhoff). More details on the system can be found in [16].

B. Validation Scenario

The same methods defined in section are implemented on the system. The parameters $\hat{\beta}^{EKF}$ are initialized in the EKF according to previous estimates [16]. We compare different cases with $R \in [R_0 \times 10^{-3}, R_0 \times 10^3]$ and $Q = \sigma_w^2 \cdot I_4$, $\sigma_w^2 \in [10^{-4}, 1]$.

C. Experimental Results and Discussion

Experimental results show that the suggested identification methods respond the same way to changes in R and Q values as described in simulations in section III-B.

Fig. 8 shows a comparison of the torques measured at the PID output with and without EKF and the torques reconstructed from the IDM using parameters identified with Methods 1 to 5 and an EKF tuning $R = R_0$ and $\sigma_w^2 = 0.09$.

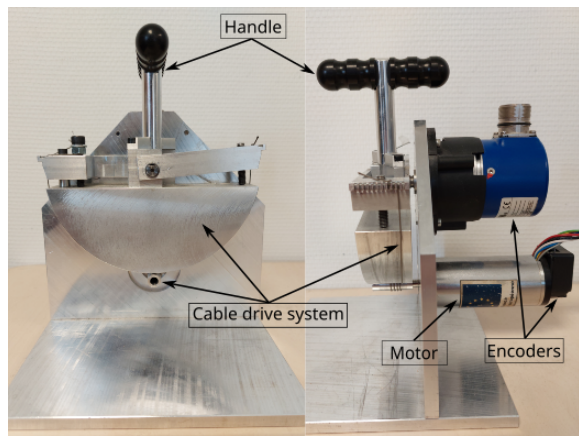


Fig. 7: System used for validation and simulation's reference.

The reconstruction is done using the measured quantized signals for Method 1, the signals out of the EKF for Methods 3 and 4, and the simulated signals out of the DIDIM process for Methods 2 and 5. We can see that the torque reconstructed from parameters estimated with Method 1 is distorted near zero velocities (around sharp changes in the torque), which is caused by a noisy computation of the velocity and its sign, affecting the friction contribution. On the contrary, Methods 3 and 4 exhibit comparable behaviors, with Method 4 reconstructing a less noisy torque due to the computation of a smoother control torque with the filtered position and velocity out of the EKF. Finally, we observe that the torques generated by Methods 2 and 5 match and are the smoothest due to the good estimation of model parameters and the use of a noise-free observation matrix.

V. CONCLUSION AND FUTURE WORKS

In this paper different methods for the identification of the dynamic parameters of a robotic system were compared, both in simulation and on a real one degree of freedom system. An extended Kalman filter (EKF) is used to estimate the position and velocity of the system from the quantized position measurements. The proposed formulation allows an intuitive tuning based on known sensor characteristics and on the confidence on the initial parameter estimations. The sensitivity of the methods to the tuning of the EKF noise covariance parameters were studied and results show that good identification of first moment and friction parameters can be obtained using least squares identification even with

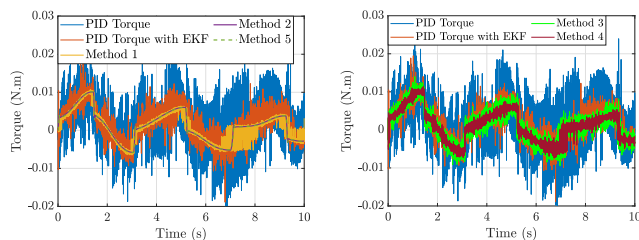


Fig. 8: Comparison of the torques measured at the PID output with (red) and without EKF (blue) and the torques reconstructed from the IDM using parameters identified with Methods 1 to 5 and an EKF tuning $R = R_0$ and $\sigma_w^2 = 0.09$.

a coarse tuning of the EKF. Inertia parameters are shown to be more sensitive to the EKF tuning in this case. Using the DIDIM identification method with the EKF proved to provide inertia estimates that are less sensitive to the tuning of noise covariance matrices but require the initial inertia estimation to be relatively close to the real value.

Future works will concern the study of an iterative tuning procedure using the identified parameters in the EKF, starting with a large value of process noise that decreases as the parameters are identified. Beyond identification, the designed EKF provides a way to obtain filtered estimations of kinematic quantities that could then be used as inputs to more complex controllers.

REFERENCES

- [1] J. Swevers, C. Ganseman, D. Tukul, J. de Schutter, and H. Van Brussel, "Optimal robot excitation and identification," *IEEE Trans. Robot. Automat.*, vol. 13, pp. 730–740, Oct. 1997.
- [2] Y. Han, J. Wu, C. Liu, and Z. Xiong, "An iterative approach for accurate dynamic model identification of industrial robots," *IEEE Trans. Robot.*, vol. 36, pp. 1577–1594, 2020.
- [3] E. Akdoğan, M. E. Aktan, A. T. Koru, M. Selçuk Arslan, M. Atlıhan, and B. Kuran, "Hybrid impedance control of a robot manipulator for wrist and forearm rehabilitation: Performance analysis and clinical results," *Mechatronics*, vol. 49, pp. 77–91, 2018.
- [4] M. Gautier, "Dynamic identification of robots with power model," in *Proceedings 1997 ICRA. IEEE International Conference on Robotics and Automation*, vol. 3, 1997, pp. 1922–1927.
- [5] M. Gautier, A. Janot, and P.-O. Vandanjon, "A new closed-loop output error method for parameter identification of robot dynamics," *IEEE Trans. Contr. Syst. Technol.*, vol. 21, pp. 428–444, Mar. 2013.
- [6] M. Pham, M. Gautier, and P. Poignet, "Identification of joint stiffness with bandpass filtering," in *Proceedings 2001 ICRA. IEEE International Conference on Robotics and Automation*, vol. 3, 2001, pp. 2867–2872.
- [7] M. Gautier and P. Poignet, "Extended kalman filtering and weighted least squares dynamic identification of robot," *Control. Eng. Pract.*, vol. 9, pp. 1361–1372, 2001.
- [8] V. Joukov, V. Bonnet, G. Venture, and D. Kulić, "Constrained dynamic parameter estimation using the extended kalman filter," in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2015, pp. 3654–3659.
- [9] B. Tout, J. Chevrier, L. Vermeiren, and A. Dequidt, "Contribution to robot system identification: Noise reduction using a state observer," in *Proceedings of the 19th International Conference on Informatics in Control, Automation and Robotics - ICINCO, 2022*, pp. 695–702.
- [10] W. Khalil and E. Dombre, "Dynamic modeling of serial robots," in *Modeling, Identification and Control of Robots*, W. Khalil and E. Dombre, Eds. Oxford: Butterworth-Heinemann, 2002, ch. 9, pp. 191–233.
- [11] I. C. Bogdan, "Modélisation et commande de systèmes linéaires de micro-positionnement : application à la production de micro-composants électroniques," Ph.D. dissertation, Univ. Paul Verlaine - Metz, Metz, Sept. 2010. [Online]. Available: <https://hal.univ-lorraine.fr/tel-01752807>
- [12] H. Mayeda, K. Yoshida, and K. Osuka, "Base parameters of manipulator dynamic models," *IEEE Trans. Robot. Automat.*, vol. 6, pp. 312–321, June 1990.
- [13] C. G. Atkeson, C. H. An, and J. M. Hollerbach, "Estimation of inertial parameters of manipulator loads and links," *Int. J. Robot. Res.*, vol. 5, pp. 101–119, 1986.
- [14] M. Brunot, A. Janot, P. Young, and F. Carrillo, "An improved instrumental variable method for industrial robot model identification," *Control. Eng. Pract.*, vol. 74, pp. 107–117, 2018.
- [15] Y. A. Shardt, X. Yang, and S. X. Ding, "Quantisation and data quality: Implications for system identification," *J Process Control*, vol. 40, pp. 13–23, 2016.
- [16] Q.-V. Dang, "Conception et commande d'une interface haptique à retour d'effort pour la cao," Ph.D. dissertation, Univ. de Valenciennes et du Hainaut-Cambresis, Valenciennes, Dec. 2013. [Online]. Available: <https://tel.archives-ouvertes.fr/tel-00985356>