# Contribution to Robot System Identification: Noise Reduction using a State Observer

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Abstract: Conventional identification approach based on the inverse dynamic identification model using least-squares and direct and inverse dynamic identification techniques has been effectively used to identify inertial and friction parameters of robots. However these methods require a well-tuned filtering of the observation matrix and the measured torque to avoid bias in identification results. Meanwhile, the cutoff frequency of the low-pass filter $f_c$ must be well chosen, which is not always easy to do. In this paper, we propose to use a Kalman filter to reduce the noise of the observation matrix and the output torque signal of the PID controller.

## 1 INTRODUCTION

Robotics applications employing model-based controllers require knowing the system parameters with high accuracy, particularly in the industrial area as stated in (Han et al., 2020) and when using impedance control techniques as described in (Akdoğan et al., 2018). In the context of rigid robotics, the conventional identification approach based on the inverse dynamic identification model (IDIM) and least-squares (LS) technique has been effectively used to identify inertial and friction parameters of many robots.

However, using sensors with large quantization steps may result in an ill-conditioned observation matrix constructed from the quantized position and its derivatives. Furthermore, the amplification of the quantization error in the integral step of the PID controller, which is commonly used to control robotic systems, results in noisy torque measurements. Because of measurement noise and incorrect data-filtering, LS parameter estimates may become extremely biased, to the point of losing all physical consistency, which can be seen in negative link masses and friction coefficients for example.

(Gautier, 1997) demonstrated that if a well-tuned filtering of the observation matrix and the measured torque is employed with LS, good identification results can be obtained. Other methods robust to noisy observation matrix were proposed such as direct and inverse dynamic identification method (DIDIM) in (Gautier et al., 2013), however they still require some low-pass filtering of the measured torque signal. In practice, the cutoff frequency $f_c$ of the low-pass filter must be well chosen. (Gautier, 1997) and (Pham et al., 2001) used the dynamic frequency $w_{dyn}$ of the robot to determine $f_c$. Nonetheless $w_{dyn}$ is not necessarily an accessible value and is not always well defined for non-linear systems. Further, (Swevers et al., 1997) and (Olsen et al., 2002) demonstrated that Maximum Likelihood identification method can significantly reduce the bias on parameter estimates in the case of noisy joint measurements, but at the cost of a greater computational effort.

In this paper, to limit the influence of quantization on the observation matrix, we consider integrating a nonlinear observer and calculating the observation matrix using the estimated position and velocity rather than the quantized position and its derivatives. Then, we propose using the estimated position and velocity as an input to the PID controller to reduce noise in the measured torque signal.

This paper is organized as follows: background and existing identification methods for robotic systems are presented in section 2. Section 3 details the proposed non-linear Kalman filtering and the usage of estimated position and velocity to improve the identification results. Then, section 4 presents simulation results for the validation of the method and discussions. Finally section 5 includes the conclusion and future works.



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# 2 BACKGROUND

## 2.1 Inverse Dynamic 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 $q, \dot{q}, \ddot{q} \in \mathbb{R}^n$. The IDM can be obtained from the Newton-Euler or the Lagrangian equations (Khalil and Dombre, 2002) 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 torque vector, and $f \in \mathbb{R}^n$ is the friction. Several friction models exist (Bogdan, 2010), a classical one is given by the following:

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

with $F_{v_j}$ and $F_{c_j}$ the viscous and Coulomb's friction coefficients of the $j$th joint respectively.

## 2.2 Model Reduction

Because the friction model in (2) is a linear function of parameters, the IDM in (1) can be expressed as a linear function of the standard dynamic parameters $\chi = \left[\chi_1^T \ \chi_2^T \ \cdots \ \chi_n^T\right]^T \in \mathbb{R}^p$ 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 $\chi_j = \left[XX_j \ XY_j \ XZ_j \ YY_j \ YZ_j \ ZZ_j \ MX_j \ MY_j \ MZ_j \ M_j \ I_{a_j} \ F_{v_j} \ F_{c_j}\right]^T$, $j = 1, 2, \cdots, n$, is the $j$th link standard dynamic parameters vector containing: $\left(XX_j,\ XY_j,\ XZ_j,\ YY_j,\ YZ_j,\ ZZ_j\right)$ the elements of the inertia tensor; $\left(MX_j,\ MY_j,\ MZ_j\right)$ the elements of the first moment; $M_j$ the link mass; $I_{a_j}$ the inertia of the actuator and transmission system; and $F_{v_j}$, $F_{c_j}$ the friction parameters.

The robot standard parameters specified in vector $\chi$ can be separated into three groups, as indicated in (Atkeson et al., 1986): identifiable, unidentifiable, and identifiable in linear combinations. The base inertial parameters $\beta \in \mathbb{R}^b$, also known as identifiable parameters, are the minimum set of inertial parameters required to construct a robot's dynamic model (Mayeda et al., 1990). (Leboutet et al., 2021) employed QR decomposition to determine $\beta$ from the set of standard parameters $\chi$ and referenced some other ways to do so.

After determining the set of base inertial parameters $\beta$, the IDM in (3) can be reduced to the minimal inverse dynamic model given by

$$\tau = IDM_{\beta}(q, \dot{q}, \ddot{q})\beta, \quad (4)$$

where $IDM_{\beta}(q, \dot{q}, \ddot{q}) \in \mathbb{R}^{n \times b}$ is the reduced model regressor. In practice, due to measurement errors and modeling uncertainties, the measured torque $\tau_m$ can be represented as follows:

$$\tau_m = IDM_{\beta}(q, \dot{q}, \ddot{q})\beta + e, \quad (5)$$

where $e \in \mathbb{R}^n$ is the error.

During an experiment, the robot is controlled to follow exciting trajectories that are optimized so that the observation matrix $W$ is well-conditioned, as described by the Fourier series in (Swevers et al., 1997), and the IDM is sampled with a sampling time $T_s$. An over-determined linear system with $r = n \cdot N$ equations and $b$ unknowns is obtained for $N$ collected samples, such that

$$Y = W(q, \dot{q}, \ddot{q})\beta + \varepsilon, \quad (6)$$

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

## 2.3 Identification Methods

### 2.3.1 Least Squares

Ordinary least squares (OLS) is a widely used method to identify robot base inertial parameters $\beta$. OLS solution $\hat{\beta}$ consists in minimizing the 2-norm of the error vector $\varepsilon$ as follows:

$$\hat{\beta} = \min_{\beta} ||\varepsilon||^2. \quad (7)$$

Solving (6) using OLS gives the following parameters estimate

$$\hat{\beta} = \left(W^T W\right)^{-1} W^T Y. \quad (8)$$

Supposing that $W$ is a deterministic matrix and $\varepsilon$ is a homoskedastic zero-mean additive independent Gaussian noise, its covariance matrix $C_{\varepsilon\varepsilon}$ is such that:

$$C_{\varepsilon\varepsilon} = E\left(\varepsilon \cdot \varepsilon^T\right) = {\sigma_{\varepsilon}}^2 \, I_r, \quad (9)$$

where $E(\cdot)$ is the expectation operator and $I_r \in \mathbb{R}^{r \times r}$ the identity matrix.

An unbiased estimation of the variance $\sigma_{\varepsilon}^2$ of the error vector $\varepsilon$ is

$$\hat{\sigma}_{\varepsilon}^2 = \frac{\left|\left|Y - W\hat{\beta}\right|\right|^2}{r - b}. \quad (10)$$

The covariance matrix $C_{\hat{\beta}\hat{\beta}} \in \mathbb{R}^{b \times b}$ of the parameter estimation error is given by

$$C_{\hat{\beta}\hat{\beta}} = E\left[\left(\hat{\beta}-\beta\right)\left(\hat{\beta}-\beta\right)^T\right], \\ = \hat{\sigma}_\varepsilon^2 \left(W^T W\right)^{-1}, \quad (11)$$

where the $i$th diagonal coefficient of $C_{\hat{\beta}\hat{\beta}}$ represents the variance $\sigma^2_{\hat{\beta}_i}$ of the $i$th estimated parameter $\hat{\beta}_i$ such that

$$\sigma^2_{\hat{\beta}_i} = C_{\hat{\beta}\hat{\beta}}(i,i). \quad (12)$$

However, if the error vector $\varepsilon$ is heteroskedastic, as is often the case in robotics since the torque noise level can be different for each joint, the weighted least squares (WLS) technique can outperform the OLS in terms of variance. This may be done by weighting (6) with a matrix $G$ of the inverse of the standard deviation of the error such that $G^T G = C_{\varepsilon\varepsilon}^{-1}$.

The WLS solution $\hat{\beta}_W$ and the estimation error covariance matrix $C_{\hat{\beta}_W\hat{\beta}_W}$ in this case can be expressed as follows:

$$\hat{\beta}_W = \left(W^T C_{\varepsilon\varepsilon}^{-1} W\right)^{-1} W^T C_{\varepsilon\varepsilon}^{-1} Y, \quad (13)$$

$$C_{\hat{\beta}_W\hat{\beta}_W} = \left(W^T C_{\varepsilon\varepsilon}^{-1} W\right)^{-1}. \quad (14)$$

OLS and WLS are non-iterative approaches that obtain base parameter estimates in a single step using measured or estimated joint torques and joint positions as illustrated in Fig. 1.

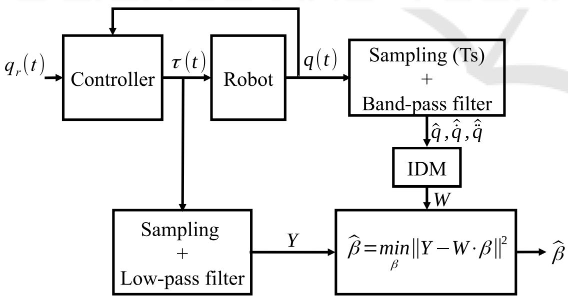


Figure 1: Least squares identification scheme of robot's base inertial parameters $\beta$ considering noisy torque measurements $\tau$ and an observation matrix $W$ computed using the inverse dynamic model (IDM) with quantized position measurements $q$ and its derivatives of velocity $\dot{q}$ and acceleration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

However, one issue with the least square (LS) methods' parameter estimations is their vulnerability to measurement noise. Indeed, LS approaches assume that the observation matrix $W$ and the error vector $\varepsilon$ are uncorrelated, which is not the case in a closed loop system having measurement noise on the position. To overcome this limitation, one option is to use data filtering (Gautier, 1997), while another is to employ identification methods that are robust to violation of this condition such as the one presented in the following.

### 2.3.2 Direct and Inverse Dynamic Identification Method

The direct and inverse dynamic identification method (DIDIM) proposed by (Gautier et al., 2013) 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.

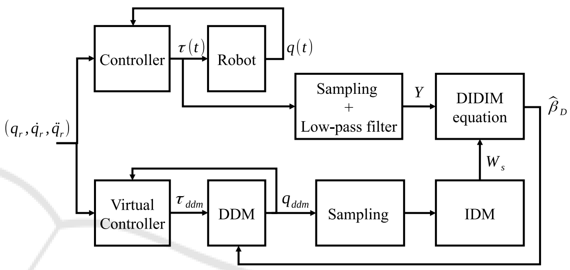


Figure 2: Direct and inverse dynamic identification method (DIDIM) scheme for identification of $\beta$ considering noisy torque measurements $Y$ and an observation matrix $W_s$ computed using the inverse dynamic model (IDM) with position $q_{ddm}$, velocity $\dot{q}_{ddm}$ and acceleration $\ddot{q}_{ddm}$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

At iteration $k$, the DIDIM estimate $\hat{\beta}_D^k$ can be identified using the following equation

$$\hat{\beta}_D^k = \left({W_s^k}^T W_s^k\right)^{-1} {W_s^k}^T Y, \quad (15)$$

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.

It is critical that the system's trajectory (position, velocity, and acceleration) do not change significantly between iterations, such that, for any $\hat{\beta}_D^k$

$$\left(q_{ddm}(\hat{\beta}_D^k), \dot{q}_{ddm}(\hat{\beta}_D^k), \ddot{q}_{ddm}(\hat{\beta}_D^k)\right) \approx (q_r, \dot{q}_r, \ddot{q}_r). \quad (16)$$

In this case, the DIDIM converges in a few iterations and in some cases in a single iteration as demonstrated in (Gautier et al., 2013).

After DIDIM convergence, the covariance matrix of the DIDIM estimate can be calculated through

$$C_{\hat{\beta}_D\hat{\beta}_D} = \left(W_s^T C_{\varepsilon\varepsilon}^{-1} W_s\right)^{-1}. \quad (17)$$

The benefit of the method is that, measurement noise filtering is no longer required for the observation matrix. Nevertheless, noise still exists in the torque measurements, therefore torque filtering is still required.

## 2.4 Data Filtering

To produce acceptable identification results in practice, due to quantification noise in position $q$ and the noise resulting from the derivative of this position to calculate the velocity $\dot{q}$ (see Fig. 4) and acceleration $\ddot{q}$, filtering the torque and the observation matrix is required when using the LS approach. Without filtering, estimations may become biased and possibly lose their physical consistency. On the contrary, the DIDIM technique just needs the measured torque provided by the the output of the PID controller frequently used in practice. Nonetheless, filtering is still required to eliminate torque noise (see Fig. 6) caused by the quantized signals used as the PID controller's input.

A simple low-pass filter is often used for filtering (Gautier, 1997), (Brunot et al., 2018). In both LS and DIDIM identification approaches, a well-tuned cut-off frequency $f_c$ is required. Studies in the literature, such as (Gautier, 1997) and (Gautier et al., 2013), use a cut-off frequency $f_c > 10\ w_{dyn}$, where $w_{dyn}$ is the system natural frequency, which is not always known and is not always well defined for non-linear systems. The nonlinear Coulomb friction may for example introduce some high frequency phenomena in the system. Furthermore, the frequency spectrum of the noise is often unknown, particularly when considering quantification noise, thus it is unclear whether or not this filtering properly removes the noise.

As a result, an alternative processing method is presented in this paper. It allows estimating better position and velocity from noisy measures using a non-linear observer, which is easier to adjust than a low-pass filter. Furthermore, the observer's output may be used as input to the PID controller instead of the quantized signals, allowing the computed torque to be less noisy.

# 3 IDENTIFICATION USING A NONLINEAR OBSERVER

## 3.1 Extended Kalman Filter

We propose using the extended Kalman filtering methods, commonly employed for state estimation, to improve identification results. In this approach, the state is considered to be $x = \left[q^T\ \dot{q}^T\right]^T \in \mathbb{R}^{2\cdot n}$. Thus, the state space model can be obtained using the DDM computed from the IDM in (1) as:

$$\dot{x} = \begin{bmatrix}\dot{q}\\ \ddot{q}\end{bmatrix} = \begin{bmatrix}\dot{q}\\ DDM_{\chi}(q,\dot{q},\tau)\end{bmatrix}, \\ = \begin{bmatrix}\dot{q}\\ M(q)^{-1}\left(\tau - C(q,\dot{q})\dot{q} - g(q) - f(\dot{q})\right)\end{bmatrix}. \quad (18)$$

The discretization of (18) leads to the state transition function:

$$x_{k+1} = x_k + \dot{x}_k(x_k, \tau_k, w_k)\cdot T_s, \quad (19)$$

where $T_s$ is the sampling time and we choose to model the process noise $w_k \sim \mathcal{N}(0_{b\times 1}, Q)$ as a non-additive noise affecting the dynamic parameters of the system, with $Q \in \mathbb{R}^{b\times b}$ its covariance matrix, such that

$$Q = \begin{bmatrix}\sigma^2_{w_1} & & (0) & \\ & \sigma^2_{w_2} & & \\ & & \ddots & \\ & (0) & & \sigma^2_{w_b}\end{bmatrix}, \quad (20)$$

where $\sigma^2_{w_i},\ i = 1,\ \cdots,\ b$, is the variance of the error on the $i$th parameter $\hat{\beta}_i$ of the estimate vector $\hat{\beta}$. We introduce a new set of noisy parameters $\underline{\hat{\beta}_i}$, that takes into account the percentage of the uncertainty on the estimated parameters $\hat{\beta}_i$ as follows:

$$\underline{\hat{\beta}_i} = (1 + w_i)\cdot\hat{\beta}_i \quad (21)$$

Choosing small values of $\sigma_{w_i}$ indicate high confidence in the current parameters estimates $\hat{\beta}$. However, large values indicate that the model is not really trustworthy.

The observation equation also known as the measurement function is given by:

$$y_k = q_k = C\cdot x_k + v_k, \quad (22)$$

where $C = [I_n\ 0_n]$ is a selection matrix and $v_k \sim \mathcal{N}(0_{n\times 1}, R)$ is an additive measurement noise, with $R \in \mathbb{R}^{n\times n}$ its covariance matrix. The benefit of this formulation is how easily the matrices $R$ and $Q$ may be adjusted based on physical considerations.

**Observer Tuning**

To use the extended Kalman filter to estimate position $q$ and velocity $\dot{q}$, the matrices $R$ and $Q$ must be fine-tuned and the state $x$ and its covariance matrix $P$ well-initialized. As the robot tracks a reference trajectory imposed by $(q_r, \dot{q}_r, \ddot{q}_r)$, the state can initially be set to $x_0 = [q_{r_0}\ \dot{q}_{r_0}]^T$ and its covariance matrix to $P_0$ containing values which represent the uncertainty on the initial values of the position and velocity, small values indicates high confidence while large values indicates low confidence.

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 (Shardt et al., 2016):

$$R = \begin{bmatrix} \sigma_{v_1}^2 & & (0) & \\ & \sigma_{v_2}^2 & & \\ & & \ddots & \\ & (0) & & \sigma_{v_n}^2 \end{bmatrix}, \text{ with } \sigma_{v_j}^2 = \frac{(Q_{quant}^j)^2}{12}, \tag{23}$$

where $Q_{quant}^j$, $j = 1, \cdots, n$ is the quantization step of the encoder of the $j$th joint.

## 3.2 Identification

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 (6) using $(\hat{q}, \hat{\dot{q}}, \hat{\ddot{q}})$ as shown in Fig. 3, where $\hat{q}$ and $\hat{\dot{q}}$ are the estimated joint position and velocity made using the previously described nonlinear observer, while $\hat{\ddot{q}}$ is the joint acceleration computed as a central difference derivative of $\hat{\dot{q}}$.

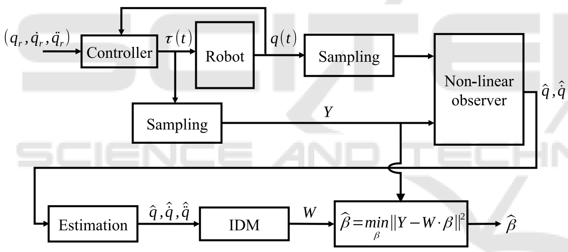


Figure 3: Least squares identification scheme of parameters β considering noisy torque measurements $Y$ and an observation matrix $W$ computed using the inverse dynamic model (IDM) with position $\hat{q}$ and velocity $\hat{\dot{q}}$ estimated using a non-linear observer.

This method is always applicable regardless of the system since it uses the measures on the system without modifying the structure of the controller. On the other hand, the PID control torque signal $Y$ still remains noisy due to the usage of the measured quantized position at the controller input. Therefore, this method cannot be used with the DIDIM approach, which uses only the torque measurements, without modification of the control structure.

In order to also reduce the torque noise, we propose to use the estimates $(\hat{q}, \hat{\dot{q}})$ as PID controller inputs as shown in Fig. 5. In such a case, identification results using LS and DIDIM techniques are expected to be improved.

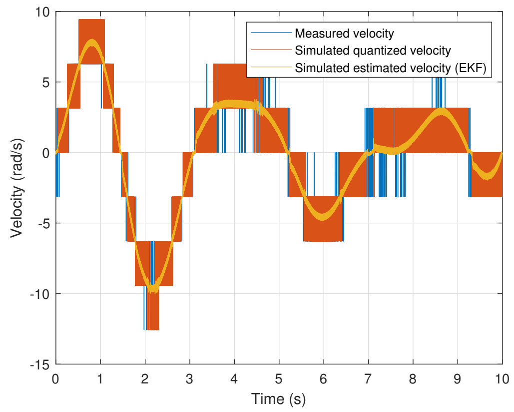


Figure 4: Comparison between measured velocity (blue), simulated quantized velocity (orange) and estimated velocity using the proposed extended Kalman filter with 30% of uncertainty on model parameters (yellow).

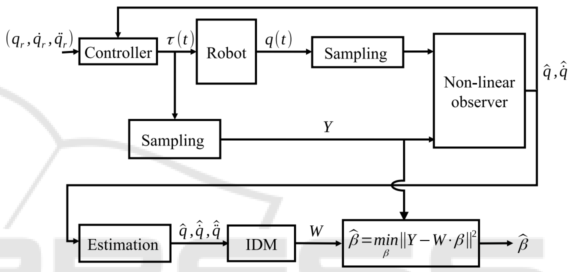


Figure 5: Least squares identification method of parameters β considering torque $Y$ computed using a modified control structure integrating the non-linear observer, and an observation matrix $W$ computed using the inverse dynamic model (IDM) with position $\hat{q}$ and velocity $\hat{\dot{q}}$ estimated using this non-linear observer.

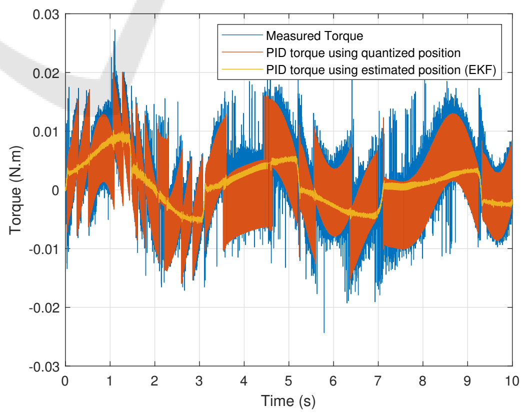


Figure 6: Comparison between measured torque (blue), simulated PID torque computed using quantized position (orange) and simulated PID torque computed using position estimated from the proposed extended Kalman filter with 30% of uncertainty on model parameters (yellow).

## 4 METHOD VALIDATION

### 4.1 Experimental Setup

Simulations were carried out in Matlab and Simulink environments to validate the suggested identification approach, utilizing a 1 DOF system simulating the real system depicted in Fig. 7. Simulations are chosen here since they provide the ground truth for the confirmation of results. The actual system is a cable-driven robot with a reduction ratio of 15. It is made up of a handle and a mass linked by a cable 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. This encoder has a resolution of 500 counts per turn, which corresponds to a quantization step $Q_{quant} = 2\pi/(500\times 4) = 0.0031416\ rad$. A PID controller implemented in an EPOS3 driver connected to the maxon motor directly controls the system. More details on the system's conception and structure can be found in (Dang, 2013).

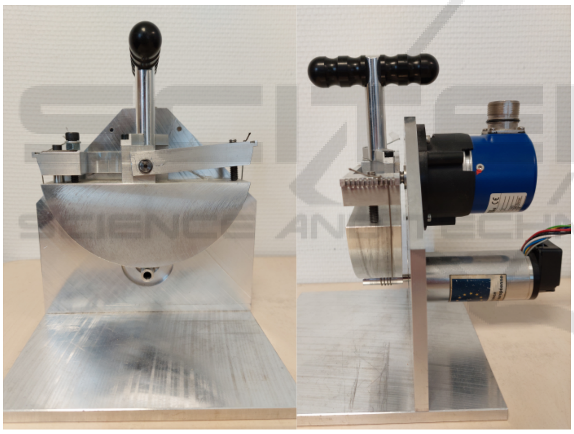

Figure 7: Handle cable-driven system with a maxon motor (EC-max 40mm, brushless 120W, model 283871) and a HEDL 5540 encoder with a resolution of 500 counts per turn controlled by an EPOS3 controller, used as the simulation's reference.

### 4.2 Validation Scenario

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

$$\tau = J\,\ddot{q} + F_v\,\dot{q} + F_c\,sign(\dot{q}) + M_s\,g\,\cos(\frac{q}{N} + q_0), \quad (24)$$

where $N$ is the reduction ratio, $g$ is the gravity, $q_0$ is the initial position of the motor shaft, $M_s \in \mathbb{R}$ is the first moment, $J \in \mathbb{R}$ is the equivalent inertia of the motor shaft and the handle, $F_v$ and $F_c \in \mathbb{R}$ are the friction coefficients defined in (2).

In this case, (19) can be written as follows:

$$x_{k+1} = \begin{bmatrix} q_k \\ \dot{q}_k \end{bmatrix} + \begin{bmatrix} \dot{q}_k \\ \frac{1}{\underline{\hat{J}}}\left(\tau_k - \underline{\hat{F}_v}\dot{q}_k - \underline{\hat{F}_c} sign(\dot{q}_k) - \underline{\hat{M}_s} g \cos(\frac{q_k}{N} + q_0)\right) \end{bmatrix} \cdot T_s, \quad (25)$$

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

According to (23), the measurement noise covariance matrix is set to $R = (0.0031416)^2/12 = 8.2247 \cdot 10^{-7}$, and the process noise covariance matrix is set to $Q = \sigma_w^2 \cdot I_4$, i.e. the same relative trust level is given to all parameters. By choosing $\sigma_w = 0.3$, we consider that our initial estimations of the parameters are within an interval of 30% of their real value.

The initial value of the state is set to $x_0 = [0\ 0]^T$, as imposed by the excitation trajectory. The position uncertainty of the covariance matrix $P_0$ is set to $R$, which represents the uncertainty of the position sensor, whereas the velocity uncertainty is set to 0.1 arbitrarily since it has influence only on the first iterations.

To evaluate the efficiency of our approach, we compare different identification methods:

- Method 1: LS with quantized data, without filtering or observation (see Fig. 1).
- Method 2: DIDIM with quantized data (see Fig. 2).
- Method 3: LS with measured torque and estimated position and velocity using the proposed EKF (see Fig. 3).
- Method 4: LS with torque computed from the position and velocity estimated using the proposed EKF (see Fig. 5).
- Method 5: DIDIM with torque computed from the position and velocity estimated using the proposed EKF.

### 4.3 Simulation Results and Discussions

Table 1 and Fig. 8 compare the identified parameters and their standard deviations, obtained using methods 1-5 with the observer regulation provided in section 4.2, to the ground-truth values. We can observe that the proposed methods 3 and 5 produce better identification results than the conventional method 1.

Method 3 actually enhances the identification results by employing the estimated position and velocity (as illustrated in Fig. 4) using the proposed EKF, allowing LS to approach the performance of the DIDIM technique defined in method 2 as well as the ground-truth values. Furthermore, method 5 results

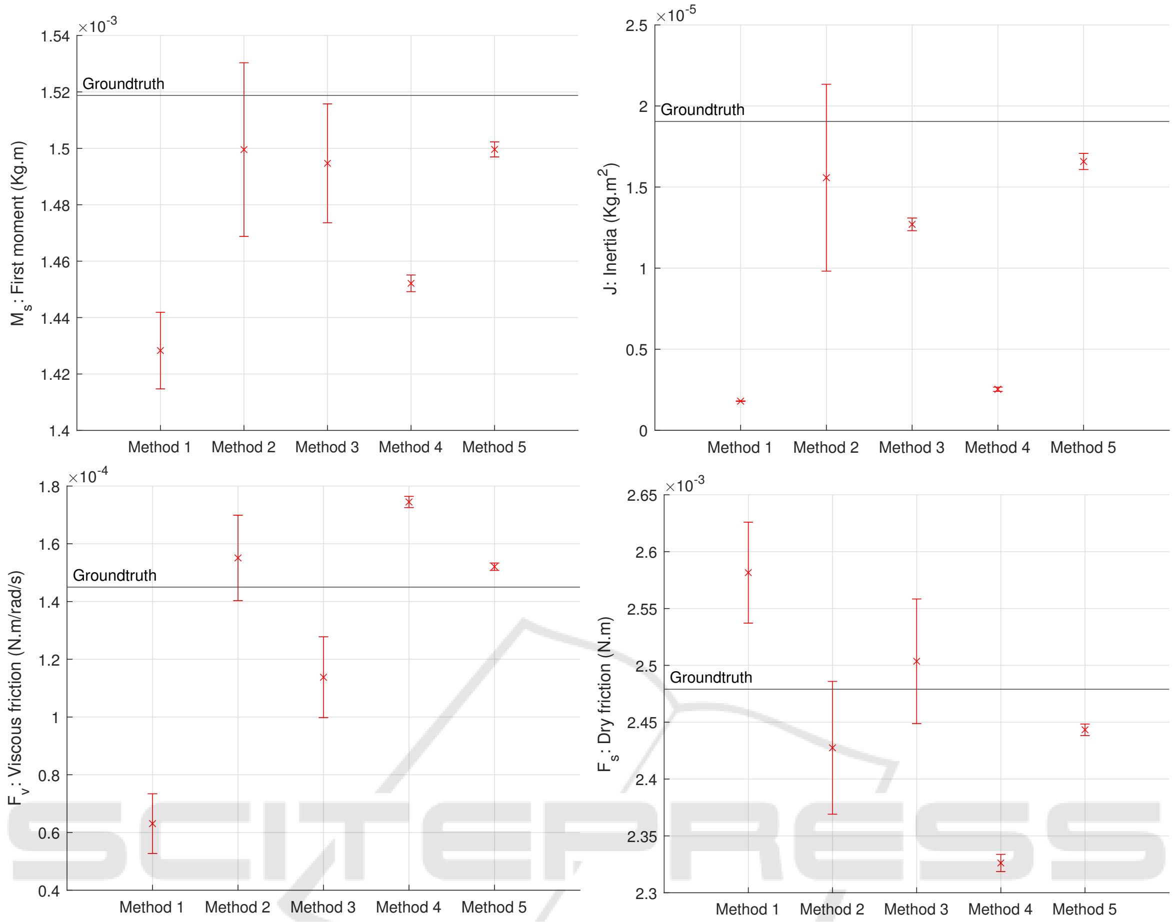


Figure 8: Comparison of identification results and standard deviation with respect to ground-truth values using the proposed extended Kalman filter having as parameters the ground-truth values with 30% uncertainty on parameters.



Table 1: Comparison of identification results and standard deviation using ideal extended Kalman filter with 30% uncertainty on parameters.

| | $M_s(Kg.m)$ | $J(Kg.m^2)$ | $F_v(N.m/rad/s)$ | $F_s(N.m)$ |
|---|---|---|---|---|
| **Ground-truth** | 1.5187E-03 | 1.9046E-05 | 1.4500E-04 | 2.4790E-03 |
| **Method 1** | 1.4283E-03 ± 1.3593E-05 | 1.7965E-06 ± 1.2876E-08 | 6.3077E-05 ± 1.0339E-05 | 2.5816E-03 ± 4.4402E-05 |
| **Method 2** | 1.4996E-03 ± 3.0773E-05 | 1.5579E-05 ± 5.7634E-06 | 1.5510E-04 ± 1.4790E-05 | 2.4275E-03 ± 5.8413E-05 |
| **Method 3** | 1.4947E-03 ± 2.1065E-05 | 1.2700E-05 ± 3.9009E-07 | 1.1378E-04 ± 1.4004E-05 | 2.5036E-03 ± 5.4817E-05 |
| **Method 4** | 1.4521E-03 ± 2.9487E-06 | 2.5303E-06 ± 1.3379E-07 | 1.7448E-04 ± 1.9369E-06 | 2.3262E-03 ± 7.5778E-06 |
| **Method 5** | 1.4996E-03 ± 2.6699E-06 | 1.6578E-05 ± 5.0017E-07 | 1.5207E-04 ± 1.2856E-06 | 2.4433E-03 ± 5.0779E-06 |

generated by DIDIM with torque computed from the estimated position and velocity using the proposed EKF (as illustrated in Fig. 6) approach the ground-truth values more closely than method 2 results obtained by DIDIM with noisy torque, and have a lower variance.

Method 4 doesn't seem to improve identification results as much as expected. This could be due to the integration of the observer in the control structure. This point should be investigated in future works.

# 5 CONCLUSIONS

This paper proposes a method for the identification of the dynamic parameters of a robotic system. The method uses an extended Kalman filter to estimate the position and velocity of the system based on the quantized position measurements. These estimates are used as inputs to the controller, resulting in a smoother torque output that can be used in the DIDIM identification method. The formulation of the filter allows an intuitive tuning based on known sensor characteristics and on the confidence on the model parameter initial estimations. A simple, one degree of freedom system is used as an illustration for the validation of the method. Simulation validation shows that the proposed method improves the identification results.

As future work we plan to validate the method on the real system as well as on more complex systems. Further study of the influence of the tuning of the extended Kalman filter will also be carried out to validate the robustness of the proposed method.

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