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Abstract

This paper brings an identified model for a 6 degrees of freedom (dof) industrial robot, the Denso VP-6242G robot, first without payload, then with a payload. This last is composed of a force sensor fixed between a spherical handle and the robot end-effector. This equipped end-effector is intended to experiments in the field of Physical Human-Robot Interactions (PHRI), for co-manipulation purposes. The control algorithms that are necessary to achieve a good PHRI, require a good knowledge of the robot dynamical model, especially the inertia matrix which should be positive definite whatever the configuration of the robot. However, most of industrial robots are supplied without any datasheet containing the inertial parameters nor Computer-Aided-Design (CAD) model. Hence, we propose to apply an identification procedure to experimental data, based on the Inverse Dynamic model Identification Method (IDIM). To ensure the positive definiteness of the inertia matrix, the used optimization step addresses the problem of nonlinear Weighted Least Squares (WLS), derived from the mathematical formulation of the identification problem, under a set of nonlinear constraints in the parameters.

keywords: Industrial Robot; Closed-Loop Identification; Constrained Optimization.

1   Introduction

In control engineering field, most of the advanced nonlinear control techniques require the knowledge of the system's dynamical model. It is the case for many control problems concerning industrial robot manipulators, for which good trajectory tracking has to be carried out. Many works about Physical Human-Robot Interactions (PHRI) rely on the principle of trajectory tracking, as in [Jlassi et al., 2014]. In these papers, the authors worked on the co-manipulation problem, which consists in achieving a master-slave relationship between an industrial robot and a human operator (HO), while making the PHRI safe and transparent for the HO. A dynamical model contains kinematic and dynamic parameters. The kinematic parameters are known as the parameters of the Modified Denavit-Hartenberg convention (MDH) [Khosla and Kanade, 1985]. It is not difficult to extract these latter based on the robot datasheet provided by the manufacturers. However, dynamic parameters, which are inertial and friction parameters, are rarely available in such datasheet. Also, it is difficult, say impossible, to get a Computer-Aided-Design (CAD) model in order to obtain a good approximation of some inertial parameters. Then, the use of identification techniques applied to experimental data [Walter and Pronzato, 1997] become the only way to get a good dynamical model. This topic has received a great attention by the robotics community during the last thirty years. Several important issues have been addressed by researchers. A non exhaustive list of issues can be found in [Swevers et al., 2007]. Among them, the obtaining of a parametrized dynamical model is of utmost importance because it determines the number of parameters to be estimated. This issue has raised a great number of works that has lead the researchers to distinguish between the notions of *base parameters* and *link inertial parameters*. These keywords were introduced in [Gautier and Khalil, 1990, Gautier, 1990]. Basically, the *base parameters* are a kind of parameters' regrouping within the motion equations, that allows to formulate these motion equations as a linear relation in these parameters. This turns out to be useful when deriving an algorithm of parameters' estimation. Another issue concerns the experimental design, including the robot excitation [Jin and Gans, 2015]. Most of people suggested a data acquisition in closed-loop, using a joint-position control with a simple proportional controller designed to ensure a desired trajectory tracking. Even if the closed-loop feature creates some correlations between the noise affecting the measurements and the other signals within the closed-loop structure, this approach turns out to be quite efficient in the parameters' estimation if the measured signals are well post-processed with a suitable filtering [Janot et al., 2014, Brunot et al., 2017]. The desired trajectories are almost always taken as a sum of sinusoids with appropriate magnitudes, phases and frequencies, in order to maximize the Signal-to-Noise-Ratio (SNR) during the acquisition and to provide a persistent excitation, which ensures the parameters' identifiability. Finally, the estimated parameters' computation method is closely related to the kind of model used for identification. The Inverse Dynamic model Identification Method (IDIM) is the most popular one since it provides an equivalent formulation of the torques that is linear in the *base parameters*. Hence, the Least Squares (LS)

algorithm can easily be performed [Swevers et al., 2007, Jin and Gans, 2015, Vuong and Jr., 2009]. Most of works have rather used the Weighted Least Squares (WLS) technique to prevent the effects of inaccurate data. Nevertheless, there is no guarantee that the estimated parameters lead to a positive definite inertial matrix [Yoshida and Khalil, 2000].

In this paper, we propose to combine a nonlinear WLS estimation technique under a set of nonlinear constraints in the dynamic parameters, that ensures the inertia matrix to be positive definite. The paper is organized as follows: Section 2 introduces the basics on robot identification. It explains the used method based on a constrained nonlinear WLS. Then, Section 3 proposes the application of this method to the Denso VP-6242G robot, in order to identify a model of the robot with and without a payload. Finally, Section 4 concludes this paper.

2 Basics on robot identification

Consider the general case of a rigid robot composed of n revolute joints, n serial links and a fixed base. The kinematic parameters are assumed to be well known. The *dynamic parameters* stands for the *inertial parameters* of the links as defined by [Yoshida and Khalil, 2000], and the usual *Coulomb & viscous* friction coefficients as indicated in [Swevers et al., 2007]. A parametric equation of motion in these parameters can be formulated, in continuous time, as:

$$M(q,\theta)\ddot{q} + N(q,\dot{q},\theta) = \tau, \tag{1}$$

where q, $\dot{q}$ and $\ddot{q}$ denote the $(n \times 1)$ vectors of joint positions, velocities and accelerations respectively, called kinematic joint variables. τ is the $(n \times 1)$ vector of joint torques; $M(q,\theta)$ denotes the $(n \times n)$ inertia matrix which is symmetric and positive definite; $N(q,\dot{q},\theta)$ is the $(n \times 1)$ vector that gathers the Coriolis, centrifugal, gravity and friction torques. Both terms depend on the *dynamic parameters*' vector denoted θ, of dimension $(n_\theta \times 1)$, in a linear manner. It is assumed that all the components of q and τ are measured with noisy sensors.

2.1 Choice of the parameters for the IDIM approach

The IDIM consists in rewriting the left side of (1) as a linear relation in θ as follows:

$$\tau = D(q,\dot{q},\ddot{q})\theta. \tag{2}$$

where D is a $(n \times n_\theta)$ matrix that only depends on the joint variables of the robot, called the measurements matrix [An et al., 1985]. By using the same notations as [Khalil and Creusot, 1997] for the link i, we can define the following dynamic parameters:

- xx_i, xy_i, xz_i, yy_i, yz_i, zz_i are the components of the inertia tensor matrix ^iI_i around the origin O_i of the link frame R_i;

- mx_i, my_i, mz_i are the first moments;

- m_i is the mass of the link;

- Fs_i, Fv_i are the Coulomb and viscous friction coefficients of a friction model linear in these parameters.

The above parameters are gathered in the following vector:

$$\theta_i^T = \begin{bmatrix} xx_i & xy_i & xz_i & yy_i & yz_i & zz_i \\ mx_i & my_i & mz_i & m_i & Fs_i & Fv_i \end{bmatrix}. \tag{3}$$

where ^{T} denotes the transpose operator, and θ is built by concatenating the θ_i $(i = 1, ..., n)$. The first ten parameters of θ_i are called the *inertial parameters* for the link i, as indicated by [Yoshida and Khalil, 2000].

In [Gautier and Khalil, 1990, Gautier, 1990], the authors have proposed to determine which are the parameters that have no influence on the dynamics of the robot. They derived some rules for the regrouping of the inertial parameters and the corresponding relationships. The regrouped inertial parameters are called *minimum inertial parameters*. The new parameter vector is called the *base parameter* vector θ_B of n_{θ_B} components. Relation (2) can be rewritten as

$$\tau = D_B(q, \dot{q}, \ddot{q})\theta_B, \tag{4}$$

where D_B is a $(n \times n_{\theta_B})$ matrix, with $n_{\theta_B} < n_\theta$.

2.2 Closed-loop data acquisition and excitation signals

For the sake of preserving the robot integrity, it is matter to drive the robot while mastering its configuration at each sampling time, in order to avoid self collisions or collisions of the robot with its environment. Hence, a joint position feedback control with a simple proportional controller, with suitable adjusted gains, is performed to follow a given trajectory in joint space that meets some desired requirements. In identification, the choice of the excitation signal is important, because it should allow that "all the parameters to estimate are excited". A signal with this feature is called a Persistent Excitation Signal (PES). A PES used to identify n_{θ_B} parameters must contains at least n_{θ_B} sinusoids of different frequencies [Walter and Pronzato, 1997], [Gautier and Khalil, 1988], [Lennart, 1971]. In addition, the desired trajectory should be designed so that it is periodic during a long time range with a number of period grater than n in order to allow the statistical analysis of the results [Swevers et al., 2007]. Moreover, the values taken by the designed position trajectories should comply with the robot allowable limit range of motion, and at the same time maximize the Signal-to-Noise-Ratio (SNR) of the interesting measured signals. Such generated signals are typically used in identification as desired trajectories for the joint positions. If the proportional gains are high enough, then the tracking errors between the measured joint positions and the desired ones are small enough to consider them having similar properties than the desired periodic trajectories, each trajectory being built to be a PES.

2.3 Signal processing

Because of the noises that affect the sensors, the measured data (joint torques and positions) can not be directly used in identification because of the closed-loop feedback control that might creates correlations between the noises and the signals of the closed-loop system. This can strongly influence the values of parameters to identify [Brunot et al., 2017]. To attenuate the undesirable effects of noise on the estimated parameters, it is matter to filter these data before their use in the estimation procedure. This is done off-line thanks to a low-pass filter with a unit gain at low frequencies and a frequency cut-off roughly set a decade after the highest existing frequency in the desired trajectories. To avoid the drawbacks that are inherent to causal linear filtering, a forward plus backward filtering of the noisy data is performed to get a zero-phase filtering of all the measurements. Furthermore, since the applied excitation signals contain many periods, an average period of each signal is computed over all the available periods in order to reduce the computational burden of the estimation algorithm and to provide statistical information about the estimation confidence. Given a periodic signal in discrete time, denoted $s(t)$, with P full periods K samples per period. The average period of $s(t)$, denoted by $\bar{s}(t)$ is computed as follow:

$$\bar{s}(t) = \frac{1}{P} \sum_{p=1}^{p=P} s(t + K(p-1)). \tag{5}$$

Finally, to reduce the computational burden, it may be useful to undersample the data if the sampling frequency is very higher than the frequency bandwidth.

Let $\hat{\tau}$ and $\hat{q}$ be the resulting joint torques and positions after applying all the signal processing steps described before; $\dot{\hat{q}}$ and $\ddot{\hat{q}}$ are the resulting joint velocities and accelerations, computed by a suitable numerical differentiation of $\hat{q}$ and a

zero-phase filtering to reduce the numerical noises. Assume the data contains N samples per period for each of these variables. These data are assumed to check the following relation at sample time t, derived from (4)

$$\hat{\tau}(t) = D_B \left(\hat{q}(t), \dot{\hat{q}}(t), \ddot{\hat{q}}(t) \right) \theta_B + \rho(t) \tag{6}$$

where ρ is an $(n \times 1)$ vector of error terms, gathering the noises and the unmodelled phenomena. It is assumed to have a zero-mean, and uncorrelated samples. The sets of N samples kept after the whole signal processing described above are used to define:

$$Y := \begin{bmatrix} \hat{\tau}(1) \\ \vdots \\ \hat{\tau}(N) \end{bmatrix}, W := \begin{bmatrix} D_B \left(\hat{q}(1), \dot{\hat{q}}(1), \ddot{\hat{q}}(1) \right) \\ \vdots \\ D_B \left(\hat{q}(N), \dot{\hat{q}}(N), \ddot{\hat{q}}(N) \right) \end{bmatrix}, R := \begin{bmatrix} \rho(1) \\ \vdots \\ \rho(N) \end{bmatrix}, \tag{7}$$

where Y, R are $(nN \times 1)$ vectors, and W is $(nN \times n_{\theta_B})$ matrix. Then, by using these new variables, (6) becomes

$$Y = W\theta_B + R, \tag{8}$$

which is an overdetermined set of linear equations in the unknown parameters in θ_B. It is worth at noting that the conditioning number of the regressor matrix W allows to measure the sensitivity of the solution θ_B to the residual noises affecting the data in $\hat{\tau}$, $\hat{q}$, $\dot{\hat{q}}$ and $\ddot{\hat{q}}$. Therefore, the signal processing step should reduce as much as possible this indicator while ensuring the convergence of the identification procedure toward a vector of parameters that is unbiased and plausible [Janot et al., 2014].

2.4   Estimation of the base parameter vector

By assuming that W is of full rank and that the components of R are independent and form a zero-mean Gaussian sequence, an estimation $\hat{\theta}_B$ of θ_B can be obtained by solving the following constrained WLS optimization problem:

$$\hat{\theta}_B = \arg\min_{\theta_B} \| W^T \Sigma^{-1/2} (Y - W\theta_B) \|^2$$
$$\text{such that} \quad M(\hat{q}, \hat{\theta}_B) > 0. \tag{9}$$

where Σ denotes the covariance matrix of the actuator torque data, which is a block diagonal matrix composed of N matrices of dimension $(n \times n)$ and denoted Σ_t. This last corresponds to the covariance matrix of the actuator torques at the sample time t and is given by:

$$\Sigma_t = \frac{1}{(P-1)} \sum_{p=1}^{P} \left(T_p(t) - \bar{\tau}(t) \right) \left(T_p(t) - \bar{\tau}(t) \right)^T, \tag{10}$$

where $T_p(t)$ denotes the pth period at the sample time t of the torque measurements τ, on which has been applied only the filtering and the decimation steps of the signal processing procedure, say without the average computing one.

The problem (9) consists in minimizing the squared norm of the weighted error between the measured and computed joint torques, under the constraint that the reconstructed inertia matrix $M(\hat{q}, \hat{\theta}_B)$ is always positive definite, say with positive eigenvalues, whatever the robot configuration. A sufficient condition for the inertial matrix to be positive definite for each configuration of the manipulator is given in [Yoshida and Khalil, 2000]. The authors have proved that the following constraints on the link physical parameters for each link composing the manipulator, lead to a definite positive inertia matrix:

$$m_i > 0 \quad \text{and} \quad {}^iI_{g_i} > 0, \quad i = 1, \dots, n \tag{11}$$

where m_i and ${}^iI_{g_i}$ are the mass and the inertia tensor matrix around the center of mass g_i of the link i. The relation between

^iI_i and $^iI_{g_i}$ is given by [Yoshida and Khalil, 2000]:

$$^iI_i = {}^iI_{g_i} + m_i \left(r_i^T r_i E_3 - r_i r_i^T \right),\tag{12}$$

where $r_i = \begin{bmatrix} x_i & y_i & z_i \end{bmatrix}^T$ is the vector from O_i to g_i, and E_3 is the (3×3) identity matrix. The link inertial parameters of subsection 2.1 are denoted by θ_{I_i}. The base parameters' vector θ_B is a nonlinear function of θ_{I_i}, Fs_i and Fv_i denoted by

$$\theta_B = f \left(\{\theta_{I_i}, Fs_i, Fv_i\}_{i=1,\dots,n} \right),\tag{13}$$

whose expression can be derived analytically as reported in [Khalil and Creusot, 1997, Khalil et al., 2014]. Let define the *link physical parameters* θ_{P_i} as the elements of $^iI_{g_i}$, r_i and m_i. Some elements of θ_{I_i} are also in θ_{P_i} (like m_i). However, other elements have a linear (like mr_i) or nonlinear (like ^iI_i) relation with elements of θ_{P_i}. By denoting h the general relation derived from (12), between θ_{I_i} and θ_{P_i}, it comes:

$$\theta_{I_i} = h(\theta_{P_i}), \quad i = 1,\dots,n.\tag{14}$$

Using the relations (13) and (14), the base parameters' vector θ_B can be rewritten as a nonlinear function, denoted by g, of $\vartheta_i = \begin{bmatrix} \theta_{P_i}^T & Fs_i & Fv_i \end{bmatrix}^T$:

$$\theta_B = g \left(\{\vartheta_i\}_{i=1,\dots,n} \right).\tag{15}$$

According to [Yoshida and Khalil, 2000], a sufficient condition to have a positive definite inertia matrix is that all m_i and $^iI_{g_i}$ contained in (15) must satisfy the conditions in (11). However, the solutions in m_i and $^iI_{g_i}$ are not unique. In [Yoshida and Khalil, 2000], they form a set of *virtual parameters*. The problem in (9) becomes a new Constrained WLS (CWLS) optimization problem, in which the solution is sought by solving:

$$\hat{\vartheta} = \arg\min_{\vartheta} \| W^T \Sigma^{-1} (Y - Wg(\vartheta)) \|^2$$
$$\text{such that} \begin{cases} m_i > 0, & {}^iI_{g_i} > 0, \\ Fs_i > 0, & Fv_i > 0, \quad i = 1,\dots,n \end{cases}\tag{16}$$

Note that $^iI_{g_i} > 0$ is equivalent for its eigenvalues to be strictly positive. Moreover, the estimated values of Fs_i and Fv_i can only be positive, that is why these constraints have been added in (16). Finally, the estimated base parameters' vector $\hat{\theta}_B$ is obtained by substituting the estimated vector $\hat{\vartheta}$ in (15). Note that, because of its nonlinear feature w.r.t. the physical parameters, the optimization problem in (16) may contain several local minima. It should then be tackled by global optimization solvers. The global minimum seeking may be a tedious task.

2.5 Payload parameters identification

The joint torques in Y can be seen as the sum of the ones resulting from the robot bodies Y_r, and those of the robot payload Y_p [Swevers et al., 2007] (plus R the vector of unknown noises and unmodelled dynamics):

$$Y = Y_r + Y_p + R\tag{17}$$
$$= Y_r + W_p \theta_p + R,\tag{18}$$

where W_p is a $(n \times n_{\theta_p})$ regressor matrix; θ_p is a vector of parameters composed of the payload inertial parameters and the variation of joints friction parameters (ΔFs_i and ΔFv_i) for all the joints. Indeed, the friction parameters may change when a payload is added to the robot [Swevers et al., 2007]. As the frame of the payload is fixed w.r.t. the last link, W_p is composed by the columns of W which correspond to all the joint friction parameters, and to the base inertial parameters of

the last link. Note that W is the derived regressor matrix of the robot with its payload. To identify the payload parameters, the acquisition of two data series is necessary. The first corresponds to the robot without the payload, while the second is acquired for the robot with its payload. The estimation of θ_p can be obtained by solving the following problem:

$$\hat{\theta}_p = \arg\min_{\theta_p} \| W_p^T \Sigma^{-1} (Y - Y_r - W_p \theta_p) \|^2$$
$$\text{such that} \quad \begin{cases} m_p > 0, & {}^n I_{g_p} > 0, \\ \Delta F s_i > 0, & \Delta F v_i > 0, \quad i = 1, \ldots, n \end{cases} \tag{19}$$

where Y_r contains the torques data from the first data series, whereas Y and W_p contains the second data series.

2.6 Validation

To check the validity of the estimated parameters by the proposed procedure, these parameters are used to reconstruct the joint torques and compared to the measured ones. For this purpose, the joint positions, velocities and accelerations are used as inputs for the inverse dynamic model in (2) with the identified parameters. This validation step is necessary to have information about the confidence intervals of the identified parameters, and at the same time about the validity of the dynamical model of the robot.

3 Case study : Denso VP-6242G robot

3.1 Dynamic identification model of the robot

The Denso VP-6242G robot is a manipulator with six revolute joints, depicted in Figure 1. As shown in Fig. 1, the robot end-effector can be equipped with a force sensor and a spherical handle for PHRI experiments. The dynamical model is computed using the parameters of the Modified Denavit-Hartenberg convention (MDH) [Khalil and Kleinfinger, 1986]. Figure 2 shows the frames attached to each joint of the robot according to this convention. Table 1 shows the MDH parameters of the Denso VP-6242G robot, extracted from Fig. 2. By using the SYMORO+ software package

Table 1: Kinematic parameters of the Denso robot

i	α_i	d_i	r_i	θ_i	i	α_i	d_i	r_i	θ_i
1	0	0	l_{1z}	q_1	4	$-\dfrac{\pi}{2}$	$-l_{3x}$	$l_{3z} + l_4$	q_4
2	$\dfrac{\pi}{2}$	0	0	$q_2 + \dfrac{\pi}{2}$	5	$\dfrac{\pi}{2}$	0	0	q_5
3	0	l_2	0	$q_3 - \dfrac{\pi}{2}$	6	$-\dfrac{\pi}{2}$	0	l_5	q_6

[Khalil and Creusot, 1997, Khalil et al., 2014] with these parameters, the dynamic model of the robot for identification is calculated. It results in a base parameters' vector θ_B of dimension (48×1), and a regressor matrix D_B of dimension (6×48). The base parameters' vector of the payload θ_p is a (19×1) vector.

3.2 Excitation signals

The used excitation signals, for each axis, have been designed as a sum of 55 basic sinusoids of same amplitudes, random phases and different frequencies. Each resulting sum was scaled to comply with its corresponding range of joint motion (see Table 2), set to keep the robot safe. The frequencies have been chosen to be integer multiples of a fundamental
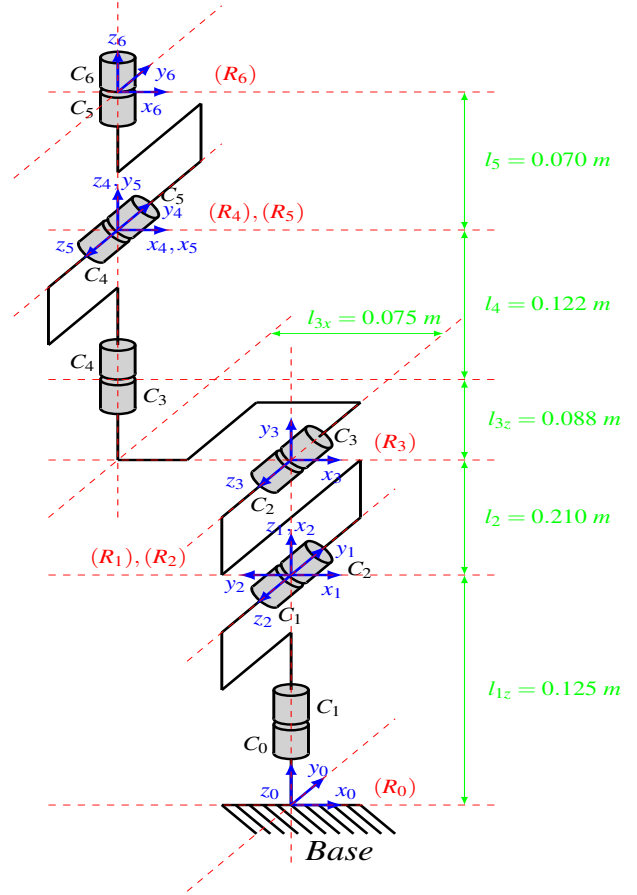
Figure 1: VP-6242G Denso robot.

Figure 2: Robot frames for MDH convention.

frequency. The number of sinusoids is greater than the number of base parameters to identify in order to obtain a PES [Lennart, 1971]. Also, all frequencies are lower than the limit frequency, defined as follow:

$$f_i = \frac{A_{\dot{q},i}}{2\pi A_{q,i}}, \tag{20}$$

where $A_{q,i}$ and $A_{\dot{q},i}$ are the maximum allowed amplitude of the joint position and velocity for the joint actuator i. The $A_{q,i}$ are determined to avoid the collisions between the robot and its environment, and the self collisions between some parts of the robot. The $A_{\dot{q},i}$ are derived from the actuator positioning time characteristic, that gives a relation between positioning time and motion angle, according to the weight of the load carried by the manipulator. These excitation signals are used as desired inputs for the robot in closed-loop, through a joint position feedback control with proportional gains. To have a more accurate estimation, the excitation signals are created with 12 periods, with 380 sec per period. This number of periods is greater than $n = 6$, which allows to compute the square root inverse of the covariance matrix. The sampling time is 10^{-3} sec. The duration of one period depends on the fundamental frequency and on the limit frequency. To ensure that the robot does not exceed the range of joint motion, the initial joint positions are set in the middle of this range. In addition, the movement starts and stops with zero joint velocities and accelerations. For this, a phase of immobility of 4 sec is added at the beginning and at the end of the movement. During this phase, the robot remains at its initial position. A connection phase of 5 sec is also inserted to connect the initial joint position of the robot with the excitation signals. The total excitation time is of 4578 sec. Table 2 presents the range of the joint motion $[q_{i,m}, q_{i,M}]$, the amplitudes $A_{q,i}$, $A_{\dot{q},i}$, the limit frequencies f_i and the proportional gain K_{p_i} of the joint-position controller for each axis J_i.

Table 2: Features for the excitation signals' design

Axis	$[q_{i,m}, q_{i,M}]$ [°]	$A_{q,i}$ [°]	$A_{\dot{q},i}$ [°/s]	f_i [Hz]	K_{p_i}
J_1	$[-135, +135]$	135	±168.7882	0.1989	1.2838
J_2	$[-45, +90]$	67.5	±126.4223	0.2981	1.6683
J_3	$[-90, -40]$	25	±168.3147	1.0715	4.4711
J_4	$[-155, +155]$	155	±202.1053	0.2075	1.3116
J_5	$[-90, +90]$	90	±205.1282	0.3627	1.7577
J_6	$[-160, +160]$	160	±203.6364	0.2025	1.6678

3.3 Data processing

First, the measurements of the joint currents and positions are recorded. To obtain joint torques, the joint currents are multiplied by their corresponding torque constants K_{c_i} and motor gear ratios G_{r_i}, presented in table 3. Then, the data are

Table 3: Motor specifications for the studied robot

Axis	J_1	J_2	J_3	J_4	J_5	J_6
K_{c_i}	0.38	0.38	0.22	0.21	0.21	0.21
G_{r_i}	120	160	120	100	100	100

filtered by using a low-pass Butterworth filter, with a cut-off frequency of 10 Hz, and of order 1. Joint velocities and accelerations are computed by a suitable numerical differentiation of the filtered joint positions. To reduce possible noises due to numerical differentiation, the velocities and accelerations signals are also filtered by the same filter. In a third step, the data corresponding to the phases of immobility and connection are deleted. The average periodic data are computed over the 12 periods as in (5). In the last step, since the sample frequency (10^3 Hz) is too high compared to the filter cutoff frequency (10 Hz), the size of the data are reduced by an undersampling of factor 10, that makes the signals with a sample frequency equal to 10^2 Hz. This frequency remains sufficiently high compared to the highest frequency contained in the data (Table 2). Hence, the data should not be affected too much by this decimation.

A zoom between the instants 1200 and 1300 sec of the signals of measured joint position and torque, and calculated velocity and acceleration of the joint 1, before and after filtering are shown by the figure 3 (corresponds to the robot with the payload). We can observe that the noisy measurements are suitably filtered. We conclude that the choice of the filter parameters (cut-off frequency and order) is good. The important error in the joint acceleration signal is interpreted by a significant noise associated with this signal, resulting from a double differentiation of the noisy joint position measurement. We consider that these post-processed data are ready to be used in the sequel of the identification procedure.

3.4 Parameters estimation

The regressor matrices and the torque vectors were built for the two cases: with and without the payload. We have checked that these matrices are of full rank. In the case of the VP-6242G Denso robot, ϑ is of dimension (66×1) and ϑ_p is (22×1). The estimation of the parameter vectors ϑ and ϑ_p consists in solving the CWLS optimization problem in (16). For this, we used a global optimization solver of Matlab, based on its function `fmincon` that allows to find a minimum solution of the CWLS problem. Table 4 shows two sets of numerical values of the base parameter vector $\hat{\theta}_B$ estimated with and without the payload robot.

Table 5 shows numerical values of the payload base parameters, containing the variation of the joint friction coefficients.
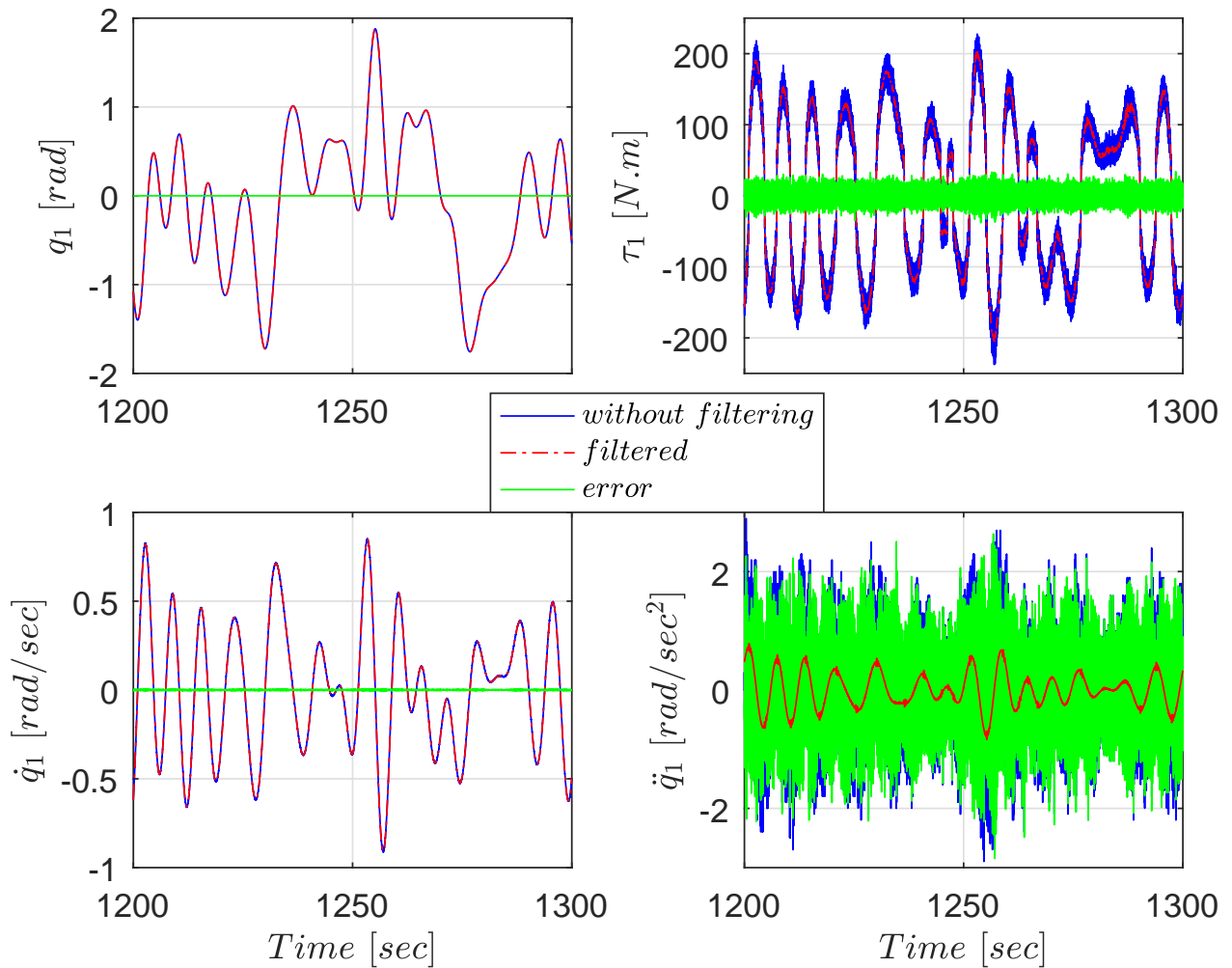
Figure 3: Data signals for axis 1 with and without processing: measured joint position and torque (top), and computed joint velocity and acceleration (bottom).

3.5 Torque reconstruction

Torque reconstruction is a step for checking the validity of the estimated parameters, and at the same time the corresponding dynamical model. For this, a different measurement series than the one exploited for the identification, but with the same features, is used. We have used two ways to reconstruct the torques of the robot with the payload. The first is by using the parameters estimated in the case of the robot with this last. The second is by using the parameters calculated without the payload, for which we add the friction variations and payload parameters, to the friction and the 6th link parameters, respectively. The figures in Fig. 4 show, for the six joints: the measured torques after filtering (blue); the computed torques with θ_B found with the payload robot (green); the computed torques using θ_B found without the payload robot to which is added θ_p (red). The figures in Fig. 4 illustrate a good quality of reconstruction of the torques. It is clear that the reconstruction with the parameters calculated with the payload is better than the one resulting from the added parameters, because of the number of errors sources. The dynamical model of the robot and the identified parameters can be considered acceptable and used to apply control techniques.

Table 4: Numerical values of θ_B with and without the payload.

θ_B	Without	With	θ_B	Without	With	θ_B	Without	With
zzr_1	5.16	7.10	zzr_3	3.07	4.37	xz_5	0.01	−0.02
Fs_1	47.44	49.74	mxr_3	−4.15	−5.16	yz_5	0.03	0.01
Fv_1	122.89	150.81	myr_3	5.76	8.77	zzr_5	0.28	0.56
xxr_2	−3.28	−5.96	Fs_3	52.23	54.78	mx_5	0.08	0.13
xy_2	−1.60	−1.01	Fv_3	83.55	87.92	myr_5	0.40	2.12
xzr_2	−1.30	−1.17	xxr_4	−0.16	−0.21	Fs_5	19.30	20.45
yz_2	−0.85	−0.97	xy_4	0.14	0.19	Fv_5	24.77	29.29
zzr_2	15.32	17.29	xz_4	0.25	0.23	xxr_6	−0.02	−0.07
mxr_2	16.02	18.67	yz_4	−0.03	−0.06	xy_6	−0.02	0.03
my_2	0.14	0.28	zzr_4	0.06	0.06	xz_6	−0.02	0.02
Fs_2	60.72	63.64	mx_4	0.29	0.30	yz_6	0.00	0.00
Fv_2	168.22	185.75	myr_4	0.21	0.20	zz_6	0.05	0.00
xxr_3	7.43	9.04	Fs_4	24.04	24.63	mx_6	−0.02	0.10
xyr_3	0.15	0.41	Fv_4	19.21	21.55	my_6	−0.01	−0.05
xz_3	0.07	0.05	xxr_5	0.05	0.22	Fs_6	18.72	19.08
yz_3	0.01	0.04	xy_5	0.00	0.01	Fv_6	11.85	15.74

Table 5: Numerical values of θ_p.

θ_p	Value	θ_p	Value	θ_p	Value	θ_p	Value
ΔFs_1	3.11	ΔFv_3	14.37	xxr_p	2.65	mx_p	0.43
ΔFv_1	33.35	ΔFs_4	1	xy_p	−0.20	my_p	0.05
ΔFs_2	4.48	ΔFv_4	3.61	xz_p	0.43	ΔFs_6	0.45
ΔFv_2	22.26	ΔFs_5	1.68	yz_p	0.05	ΔFv_6	4.62
ΔFs_3	2.17	ΔFv_5	4.61	zz_p	0.15		

4   Conclusion

In this paper, we were interested in identifying the dynamic parameters of the industrial manipulator robot Denso VP-6242G, with and without its handle. To this end, we have used a nonlinear weighted least squares formulation of the identification problem under nonlinear constraints in the dynamic parameters. The identified parameters and the dynamical model of the robot have been validated by the torque prediction approach. The identification method appeared to be efficient in giving parameters that lead to a positive definite inertia matrix. Future works will concern the use of the identified model of the Denso robot to achieve a PHRI for a co-manipulation purpose, as proposed in [Jlassi et al., 2014].

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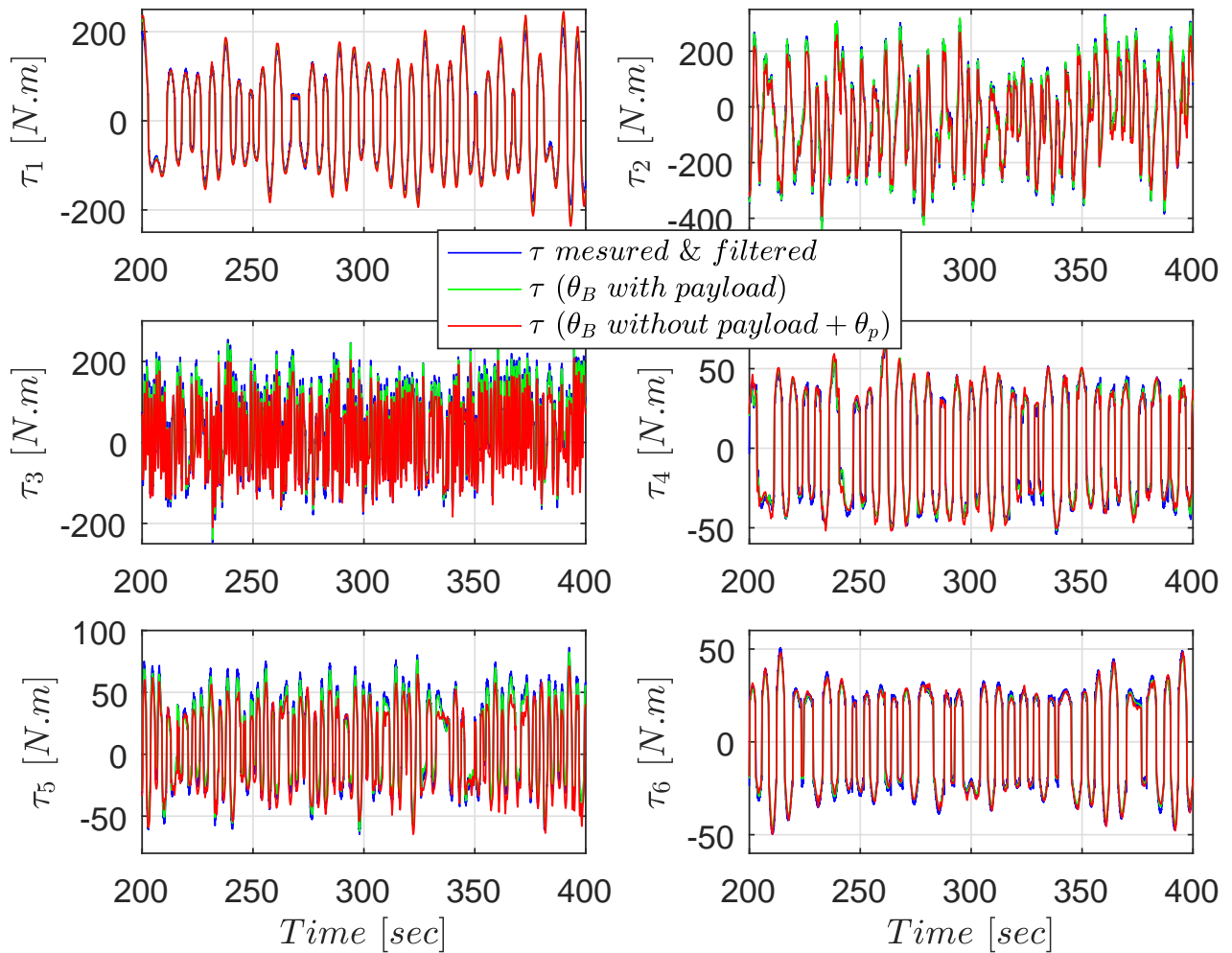
Figure 4: Comparison of the measured torques after filtering and the computed torques calculated in two ways.

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