2018 26th Mediterranean Conference on Control and Automation (MED)
Zadar, Croatia, June 19-22, 2018

Dynamic Parameters Identification of an Industrial Robot: a constrained nonlinear WLS approach

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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, with an end-effector composed of a spherical handle, fixed on a force sensor. This robot is intended to experiments in the field of Physical Human-Robot Interactions (PHRIs), 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. A validation step permits to check the efficiency of this approach for the Denso robot.**

Index Terms— **Industrial Robot; Closed-Loop Identification; Constrained Optimization.**

I. 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. This is for example the case in [1] where the authors have addressed the co-manipulation problem which consists in achieving a master-slave relationship between an industrial robot and a human operator (HO). A dynamical model contains kinematic and dynamic parameters. The kinematic parameters are known as the parameters of the Modified Denavit-Hartenberg convention (MDH) [2]. 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. Moreover, it is hard, say impossible, to get an accurate Computer-Aided-Design (CAD) model in order to obtain a good approximation of some inertial parameters. Then, the only way to get a good dynamical model is the use of identification techniques applied to experimental data, that can be found in [3]. 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 [4]. Among them, the obtaining of a dynamical model is of utmost importance because it determines the number of parameters to be estimated. This issue has lead the researchers to distinguish between the notions of *link inertial parameters* and *base parameters*, as introduced in [5], [6]. 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 [7], [8]. 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 [9], [10]. The desired trajectories are almost always designed as periodic functions, corresponding to a sum of sinusoids with appropriate features, while guaranteeing an acceptable Signal-to-Noise-Ratio (SNR) during the acquisition. This allows the inputs to meet the expected excitation properties for 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) approach can easily be performed [4], [7]. Most of works have rather used the Weighted Least Squares (WLS) technique to prevent the effects of inaccurate data. To this end, the data are averaged over one period and weighted by the covariance matrix of the torque measurements, computed by taking into account all the recorded periods. Nevertheless, there is no guarantee that the estimated parameters lead to a positive definite inertial matrix [11].

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 II introduces the basics on robot identification, and explains the constrained nonlinear WLS approach. Then, Section III proposes the application to the Denso VP-6242G robot. Finally, some conclusions are proposed in Section IV.

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978-1-5386-7891-6/18/$31.00 ©2018 IEEE

II. Basics on robot identification

Consider the general case of a rigid robot having n revolute joints, with 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 in [11], and the usual *Coulomb & viscous* friction coefficients as indicated in [4]. 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 the 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.

A. 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 kinematic joint variables of the robot, called the measurement matrix [12]. By using the same notations as in [13] 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

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

where ^{T} denotes the transpose operator. The first ten parameters of θ_i are called the *inertial parameters* for the link i, as indicated in [11]. Then, θ is built by concatenating the θ_i $(i=1,\ldots,n)$.

In [5], [6], 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 parameters' vector is called the *base parameter* vector, denoted by θ_B, and contains n_{θ_B} components. Relation (2) can thus 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 $n_{\theta_B}<n_\theta$.

B. Closed-loop data acquisition and excitation signals

For the sake of keeping the robot integrity, it is better to excite 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 gain, is performed to follow a given trajectory in joint space that meets a number of desired requirements. In identification, the choice of the excitation signal is important, because it should "excites all the parameters" to identify. 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 [14], [8], [15]. Moreover, the desired trajectory should be designed so that it is periodic during a long time range in order to ease the statistical analysis of the results [4], each period being built to be a PES and the number of periods should be greater than n. Finally, the amplitudes of the PES should be within an allowable range of motion, in order to comply with the robot safety limits, and it should maximize the Signal-to-Noise-Ratio (SNR) for each measured output signal needed for the robot identification. One can easily design such PES with the requested properties and uses them for the robot identification as desired trajectories for the joint positions. If the proportional gains of the position feedback control are high enough, then the tracking errors between the measured and the desired joint positions become small enough to ensure that the measured positions will have properties close to the ones of the desired trajectories.

C. Signal processing

In general, the measured (joint torques and positions) and computed (joint velocities and accelerations) data are noisy. These data can not be directly used in identification because of the closed-loop feedback control that might create correlations between the noises and the signals of the closed-loop system. This can introduce some unknown biases in the values of the identified parameters [10]. To avoid this undesirable effect, the data are filtered before being used by the estimation algorithms. This is done off-line thanks to a low-pass filter with a unit gain at low frequencies and a frequency cut-off set a decade after the highest existing frequency in the desired trajectories. In practice, a forward plus backward filtering of the noisy data is performed in order to get a zero-phase filtering of these data. 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. Given a periodic signal in discrete time, denoted by $x(k)$, with P full periods and K samples per period. The average period of $x(k)$, denoted by $\bar{x}(k)$, is obtained through the relation

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

Finally, it may sometimes be useful to undersample the data if the sampling frequency is too high compared to the frequency bandwidth of interest.

Let $\hat{q}$ and $\hat{\tau}$ be the joint positions and torques after applying the whole signal processing described before; $\hat{\dot{q}}$ and $\hat{\ddot{q}}$ are the resulting joint velocities and accelerations, suitably computed by numerical differentiation. The data are assumed to check the following relation at sample time k, derived from (4)

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

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

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

where Y, R are $(nN \times 1)$ vectors, and W is $(nN \times n_{\theta_B})$ matrix. Then, (6) leads to

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

which is an overdeterminated set of linear equations in the unknown parameters in θ_B.

The conditioning number associated with the regressor matrix W allows to measure the sensitivity of the solution θ_B to the noises affecting the measurements of τ, q and eventually $\dot{q}$ and $\ddot{q}$. Therefore, the post-processed data should reduce the conditioning number, to ensure the convergence of the identification process towards an unbiased vector of parameters [8], [9].

D. Estimation of the base parameter vector

For a full rank regressor matrix W, and a zero-mean additive independent Gaussian noise for R, an estimation $\hat{\theta}_B$ of θ_B can be obtained by solving the following WLS minimization problem [4]:

$$\hat{\theta}_B = \arg\min_{\theta_B} \parallel W^T \Sigma^{-1/2}\left(Y - W\theta_B\right) \parallel^2 \tag{9}$$

whose optimal solution is given by

$$\hat{\theta}_B = C W^T \Sigma^{-1/2} Y, \tag{10}$$

where Σ denotes the covariance matrix of the actuator torque data and $C := \left(W^T \Sigma^{-1/2} W\right)^{-1}$ is the covariance matrix of the estimated parameters' vector. The matrix Σ is a block diagonal matrix composed of N matrices of dimension $(n \times n)$ and denoted Σ_k, corresponding to the covariance matrix of the actuator torques computed at the sample time k. Its expression is given by:

$$\Sigma_k = \frac{1}{(P-1)} \sum_{p=1}^{P} \left(T_p(k) - \hat{\tau}(k)\right)\left(T_p(k) - \hat{\tau}(k)\right)^T, \tag{11}$$

where $T_p(k)$ stands for the p^{th} period at the sample time k of the torque measurements τ, on which has been applied only the filtering and the decimation steps. The computation of $\hat{\theta}_B$ using the relation (10) is very tractable, but this solution does not ensure that the corresponding inertial matrix is positive definite. In the sequel, we consider this additional constraint to the problem in (9), which becomes:

$$\begin{aligned} \hat{\theta}_B = \arg\min_{\theta_B} \parallel W^T \Sigma^{-1}\left(Y - W\theta_B\right) \parallel^2 \\ \text{such that} \quad M(q, \hat{\theta}_B) > 0 \quad \forall q. \end{aligned} \tag{12}$$

The problem (12) consists in minimizing the squared norm of the weighted error between the measured and computed joint torques, under the constraint that the corresponding inertia matrix is always positive definite, *i.e.* 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 [11]. The authors have proved that constraints on physical parameters of the links composing the manipulator, lead to an inertia matrix which is positive definite. The link constraints in [11] are:

$$\begin{cases} m_i > 0, \quad i = 1, ..., n \\ {}^iI_{g_i} > 0, \end{cases} \tag{13}$$

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 [11]:

$${}^iI_i = {}^iI_{g_i} + m_i\left(r_i^T r_i E_3 - r_i r_i^T\right), \tag{14}$$

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.

Let us denote the link inertial parameters mentioned in subsection II-A by θ_{I_i}. The base parameters vector θ_B is a function of θ_{I_i}, Fs_i and Fv_i $(i = 1, \ldots, n)$, whose expression can be derived analytically. Hence,

$$\theta_B = f\left(\{\theta_{I_i}, Fs_i, Fv_i\}_{i=1,\ldots,n}\right). \tag{15}$$

Let us define the *link physical parameters* θ_{P_i} as the vector whose components are the elements of ${}^iI_{g_i}$, r_i and m_i. Some components of θ_{I_i} are also included in θ_{P_i}, like m_i. However, other components of θ_{I_i} depend linearly (like mr_i) or nonlinearly (like ${}^iI_i$) in the components of θ_{P_i}. By denoting h the general relation derived from (14), between the vectors θ_{I_i} and θ_{P_i}, it follows:

$$\theta_{I_i} = h(\theta_{P_i}), \quad i = 1, \ldots, n. \tag{16}$$

Using the relations (15) and (16), the base parameters vector θ_B can be rewritten as a nonlinear function, denoted by g, of $\vartheta_i^T := \begin{bmatrix} \theta_{P_i}^T & Fs_i & Fv_i \end{bmatrix}$:

$$\theta_B = g(\{\vartheta_i\}_{i=1,\ldots,n}). \tag{17}$$

According to [11], to have a positive definite inertia matrix, it is sufficient that all m_i and ${}^iI_{g_i}$ contained in the equation (17) satisfy the condition (13). However, the set of admissible m_i and ${}^iI_{g_i}$ is not unique. In [11], it is called *virtual parameters*. The problem (12) is transformed into a Constrained WLS (CWLS) optimization new problem in the unknown parameter vector $\vartheta^T = \begin{bmatrix} \vartheta_1^T & \cdots & \vartheta_n^T \end{bmatrix}$:

$$\begin{aligned} \hat{\vartheta} = \arg\min_{\vartheta} \parallel W^T \Sigma^{-1}\left(Y - W g(\vartheta)\right) \parallel^2 \\ \text{such that} \begin{cases} m_i > 0, \quad {}^iI_{g_i} > 0, \\ Fs_i > 0, \quad Fv_i > 0, \quad i = 1, ..., n. \end{cases} \end{aligned} \tag{18}$$

The constraint on the estimated inertia tensor matrix is equivalent for this last to have all its eigenvalues positive. The estimated values of Fs_i and Fv_i can only be positive, which justifies the addition of constraints on these parameters in (18). To finish the procedure, the estimated vector $\hat{\vartheta}$ is substituted into (17) to obtain the corresponding estimation of the base parameter vector $\hat{\theta}_B$, needed to build the estimated inertia matrix. Because of its nonlinear feature, it is worth noting that the optimization problem in (18) may contain several local minima. It should then be tackled by global optimization solvers. The global minimum seeking may be a tedious task.

E. Validation

To check the validity of the estimated parameters by the proposed procedure, these parameters are used to reconstruct the joint torques which are compared with the measured ones. For this purpose, the post-processed kinematic joint variables are used as inputs for the inverse dynamic model in (2) with the estimated parameters. This validation step is necessary to have an information about the confidence interval of the estimated parameters, and at the same time, about the model validity.

III. Case study : Denso VP-6242G robot

A. Dynamic identification model of the robot

The Denso VP-6242G robot is a manipulator with six revolute joints, depicted in Fig. 1.

Fig. 1. VP-6242G Denso robot.

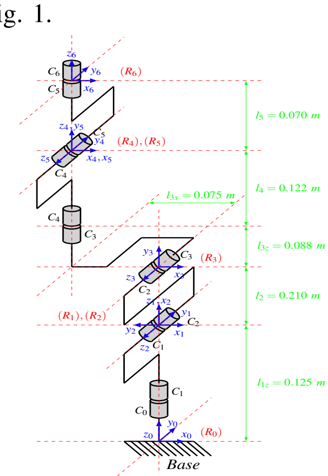

Fig. 2. Robot frames for MDH convention.

A force sensor is fixed between a spherical handle, devoted to PHRI experiments, and the end-effector. The dynamic model is computed by using the parameters of the Modified Denavit-Hartenberg convention (MDH) [16]. Figure 2 shows the frames attached to each joint of the robot according to this convention. Table I shows the MDH parameters of the Denso VP-6242G robot, extracted from Fig. 2. By using the SYMORO+ software package [13], [17] with these parameters, the dynamical model of the robot for the identification is obtained. The base parameters vector θ_B is of dimension (48×1), and the regressor matrix D_B is of dimension (6×48).

TABLE I

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	$-\frac{\pi}{2}$	$-l_{3x}$	$l_{3z}+l_4$	q_4
2	$\frac{\pi}{2}$	0	0	$q_2+\frac{\pi}{2}$	5	$\frac{\pi}{2}$	0	0	q_5
3	0	l_2	0	$q_3-\frac{\pi}{2}$	6	$-\frac{\pi}{2}$	0	l_5	q_6

B. Excitation signals

The used excitation signals, for each axis, have been designed as a sum of 55 basic sinusoids of same amplitudes, randomic phases and different frequencies. Each resulting sum was scaled to comply with its corresponding range of joint motion (see Table II), set to keep the robot safe. The frequencies have been chosen to be integer multiples of a fundamental frequency. The number of sinusoids has been taken greater than the number of base parameters to identify in order to ensure the PES's feature [3], [15]. In addition, the higher frequency was constrained by the limit frequency, defined by:

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

where $A_{q,i}$ and $A_{\dot{q},i}$ are the maximum allowed amplitudes for the joint position and velocity of the joint 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 given in the Denso Robot datasheet, that gives a relation between positioning time and motion angle, for a given load carried by the end-effector. To enhance the estimation reliability, the periodic excitation signals have been built with 12 periods, with 380 *sec* per period, and a sampling time of 10^{-3} *sec*. The duration of one period depends on the fundamental frequency and on the limit frequency. Each initial joint position is set to the center of its corresponding joint motion range. In addition, the movement starts and stops with zero joint velocities and accelerations. For this, a phase of immobility of 4 *sec* is appended at the beginning and at the end of the periodic signals. During these phases, the robot remains at the initial position. A connection phase of 5 *sec* is also appended to connect the initial joint positions of the robot with the excitation signals. The total excitation time is 4578 *sec*. Table II presents the joint motion range $[q_{i,m}, q_{i,M}]$, the amplitudes $A_{q,i}$ and $A_{\dot{q},i}$, the limit frequency f_i, and the proportional gain K_{p_i} of the joint-position controller for each axis J_i.

C. Data processing

First, the measurements of the joint currents and positions are recorded. To obtain the 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 III. Then, the data are filtered by using a zero-phase filtering through a low-pass Butterworth filter of order 1 with a cut-off frequency set to 10 Hz. Joint velocities and accelerations

TABLE II

PARAMETERS USED TO GENERATE THE INPUTS.

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	$\pm$168.7882	0.1989	1.2838
J_2	$[-45, +90]$	67.5	$\pm$126.4223	0.2981	1.6683
J_3	$[-90, -40]$	25	$\pm$168.3147	1.0715	4.4711
J_4	$[-155, +155]$	155	$\pm$202.1053	0.2075	1.3116
J_5	$[-90, +90]$	90	$\pm$205.1282	0.3627	1.7577
J_6	$[-160, +160]$	160	$\pm$203.6364	0.2025	1.6678

TABLE III

FEATURES OF THE MOTORS OF THE DENSO VP-6242G 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

are computed by a suitable numerical differentiation of the filtered joint positions. To reduce the noises due to numerical differentiation, the resulting velocity and acceleration signals are also filtered in the same way. In a third step, the data corresponding to the phases of immobility and connection are withdrawn in order to keep only the periodic parts of the data. The data are then averaged over the 12 periods. In a last step, since the sample frequency (10^3 Hz) is higher than the filter cutoff frequency (10 Hz), the data are undersampled with a factor of 10, which reduce the size of the useful data, but also the sample frequency of these data to 10^2 Hz. This frequency remains comfortably higher than the highest frequency contained in the filtered data (Tab. II). Hence, the data should not be affected a lot by this decimation factor. A zoom between the instants 1200 and 1400 *sec* of the signals of measured joint position and torque, and calculated velocity and acceleration of the joint 1, before (blue) and after (red) filtering are shown by the figure 3. We can observe that the noisy measurements are correctly

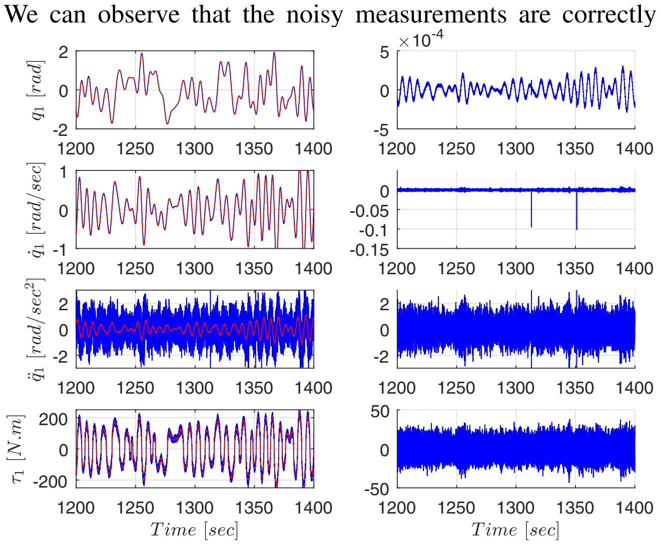

Fig. 3. Data for axis 1 before (blue) and after (red) filtering (left), and the corresponding signal errors (right).

filtered. We conclude that the choice of the filter parameters (cut-off frequency and order) is adequate. The important error in the joint acceleration signal is interpreted by a significant noise associated with this signal, as it results from a double differentiation of the joint position. We consider that these post-processed data can be used in the sequel of the identification procedure.

D. Parameters estimation

Once the regressor matrix W, the covariance matrix of the torque data Σ and the torque vector Y has been constructed, the condition number of W was checked as well as its full rank feature. In the case of the VP-6242G Denso robot, ϑ is of dimension (66×1). The estimation of the parameter vector ϑ was performed by solving the CWLS optimization problem in (18). For this, we used the Matlab function `fmincon` that allows to find a minimum solution of the constrained nonlinear multivariable problem.

The table IV shows two sets of numerical values of the base parameter vector θ_B estimated by solving the WLS problem in (10) and the CWLS one in (17) & (18). The third column of the table presents the standard deviation σ of the estimated parameter vector, defined as the squared root of the diagonal elements of the matrix C.

TABLE IV

NUMERICAL VALUES OF θ_B AND STANDARD DEVIATION OF PARAMETERS σ.

θ_B	CWLS	WLS	σ	θ_B	CWLS	WLS	σ
zzr_1	7.10	9.05	$3.64e-2$	yz_4	-0.06	-0.07	$2.83e-3$
Fs_1	49.75	49.38	$7.68e-3$	zzr_4	0.06	-0.86	$5.71e-3$
Fv_1	150.81	151.39	$2.78e-2$	mx_4	0.30	0.24	$7.84e-4$
xxr_2	-5.96	0.20	$4.46e-2$	myr_4	0.20	0.20	$6.08e-4$
xy_2	-1.01	-1.22	$2.15e-2$	Fs_4	24.63	24.62	$4.75e-3$
xzr_2	-1.17	-1	$1.35e-2$	Fv_4	21.55	21.17	$1.13e-2$
yz_2	-0.97	-0.81	$2.19e-2$	xxr_5	0.22	0.29	$4.87e-3$
zzr_2	17.29	17.71	$2.56e-2$	xy_5	0.01	0.013	$2.42e-3$
mxr_2	18.67	18.77	$2.54e-3$	xz_5	-0.02	-0.01	$1.73e-3$
my_2	0.28	0.31	$1.22e-3$	yz_5	0.01	0.01	$2.06e-3$
Fs_2	63.64	64.61	$1.12e-2$	zzr_5	0.56	0.59	$1.96e-3$
Fv_2	185.75	180.34	$4.80e-2$	mx_5	0.13	0.13	$4.58e-4$
xxr_3	9.04	-0.32	$2.89e-2$	myr_5	2.12	2.11	$4.79e-4$
xyr_3	0.41	2.27	$1.91e-2$	Fs_5	20.45	20.40	$3.79e-3$
xz_3	0.05	0.10	$5.68e-3$	Fv_5	29.29	29.12	$9.64e-3$
yz_3	0.04	0.04	$5.97e-3$	xxr_6	-0.07	-0.08	$2.34e-3$
zzr_3	4.37	4.20	$4.14e-3$	xy_6	0.03	0.03	$1.24e-3$
mxr_3	-5.16	-4.98	$1.24e-3$	xz_6	0.02	0.02	$1.27e-3$
myr_3	8.77	8.79	$1.30e-3$	yz_6	0.00	0.00	$1.36e-3$
Fs_3	54.78	54.87	$8.10e-3$	zz_6	0.00	0.05	$2.29e-3$
Fv_3	87.92	86.78	$2.95e-2$	mx_6	0.10	0.10	$4.04e-4$
xxr_4	-0.21	0.13	$7.32e-3$	my_6	-0.05	-0.05	$3.51e-4$
xy_4	0.19	0.19	$3.34e-3$	Fs_6	19.08	19.11	$3.91e-3$
xz_4	0.23	0.21	$2.81e-3$	Fv_6	15.74	15.51	$7.91e-3$

The standard deviation σ of each parameter in Tab. IV is small enough compared to the corresponding estimated value. It means that we can be confident in the parameter estimation.

TABLE V
CHECKING OF THE CONSTRAINTS IN (13).

Link	1	2	3	4	5	6
$\lambda_{\min}\left\{{}^{i}I_{g_i}\right\}$	0.01	0.01	0.01	0.01	0.01	0.01
m_i	6.22	2.07	17.99	20.95	1.93	38.45

The table V shows, for each link i, the virtual mass m_i and the minimum eigenvalue of the virtual inertia tensor matrix ${}^{i}I_{g_i}$. This table shows that the condition (13) is satisfied, ensuring a positive definite inertia matrix derived from the estimated parameters.

E. 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 set of measurement than the one exploited for the identification is used. These new data were obtained by using a new input signal but with the same features as the one used for the identification (PES + periodic...). The feedback control is used with the same proportional gains. The obtained signals are different compared to those obtained during the identification. The post-processed joint torques are compared with those resulting from the application of the corresponding joint variables (q, $\dot{q}$ and $\ddot{q}$) on the dynamical model of the robot, using the identified parameters. In Fig. 4, the measured torques after filtering are compared with those calculated using the identified parameters.

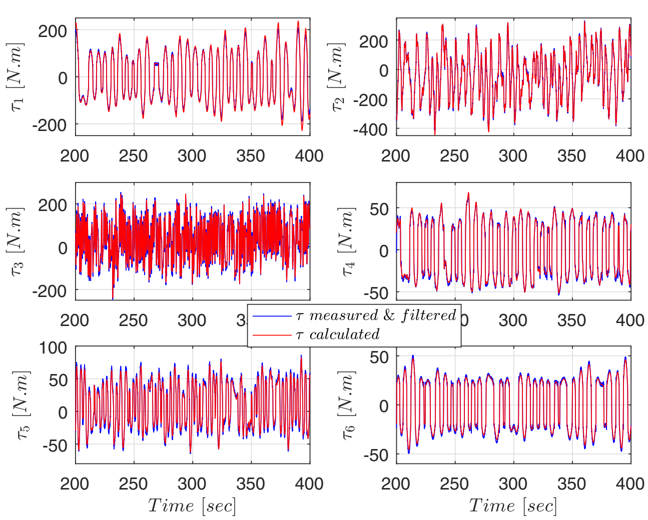

Fig. 4. The filtered measured and computed torques.

The figures in Fig. 4 illustrate a good quality of reconstruction of the torques. The dynamical model of the robot and the identified parameters can be considered acceptable and used to apply control techniques.

IV. Conclusion

In this paper, we were interested in identifying the dynamic parameters of the industrial manipulator robot Denso VP-6242G. To this end, we used a nonlinear weighted least squares formulation of the identification problem under nonlinear constraints in the dynamic parameters. The identified parameters and the dynamic model of the robot were 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 [1].

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