Global Identification of Robot Drive Gains Parameters Using a Known Payload and Weighted Total Least Square Techniques

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Abstract: Off-line robot dynamic identification methods are based on the use of the Inverse Dynamic Identification Model (IDIM), which calculates the joint forces/torques that are linear in relation to the dynamic parameters, and on the use of linear least squares technique to calculate the parameters (IDIM-LS technique). The joint forces/torques are calculated as the product of the known control signal (the current reference) by the joint drive gains. Then it is essential to get accurate values of joint drive gains to get accurate identification of inertial parameters. In the previous works, it was proposed to identify each gain separately. This does not allow taking into account the dynamic coupling between the robot axes. In this paper the global joint drive gains parameters of all joints are calculated simultaneously. The method is based on the weighted total least squares solution of an over-determined linear system obtained with the inverse dynamic model calculated with available current reference and position sampled data while the robot is tracking one reference trajectory without load on the robot and one trajectory with a known payload fixed on the robot. The method is experimentally validated on an industrial 6 joint Stäubli TX-40 robot.

1. INTRODUCTION

Several schemes have been proposed in the literature to identify the dynamic parameters of robots (Gautier and Khalil 1990), (Hollerbach *et al.* 2008), (Khalil and Dombre 2002), (Khosla and Kanade 1985), (Lu *et al.* 1993). Most of the dynamic identification methods have the following features:

- the use of an Inverse Dynamic Identification Model (IDIM) which calculates the joint force/torque linear in relation to the dynamic parameters,
- the construction of an over-determined linear system of equations obtained by sampling IDIM while the robot is tracking some trajectories in closed-loop control,
- the estimation of the parameter values using least squares techniques (LS). This procedure is called the IDIM-LS technique.

The experimental works have been carried out either on prototypes in laboratories or on industrial robots and have shown the benefits in terms of accuracy in many cases. Good results can be obtained provided two main conditions are satisfied:

- a well-tuned derivative band-pass filtering of joint position is used to calculate the joint velocities and accelerations,
- the accurate values of joint drive gains g_τ are known to calculate the joint force/torque as the product of the known control signal calculated by the numerical controller of the robot (the current references) by the joint drive gains (Restrepo and Gautier 1995).

This needs to calibrate the drive train constituted by a current controlled voltage source amplifier with gain G_i which supplies a permanent magnet DC or a brushless motor with torque constant K_t coupled to the link through direct or gear train with gear ratio N. Because of large values of the gear ratio for industrial robots, (N>50), joint drive gain, $g_\tau = NG_iK_t$, is very sensitive to errors in G_i and K_t which must be accurately measured from special, time consuming , heavy tests, on the drive chain (Restrepo and Gautier 1995), (Corke 1996).

Several papers on the topic of the joint drive gains identification have been published in the past (Corke 1996), (Gautier and Briot 2011*a,b*), (Restrepo and Gautier 1995), but all of them propose to identify each joint gain separately. This does not allow taking into account the dynamic coupling between the robot joint force/torque.

In this paper it is proposed a new method for the global identification of the joint drive gains, using current reference and position sampled data measured while the robot is tracking one reference trajectory without load fixed on the robot and one trajectory with a known payload fixed on the robot. Contrary to the previous works, all drive gains are calculated in one step by the weighted total LS solution (WTLS) of an over-determined system in order to take into account the coupling between the robot axes. The method is experimentally validated on a 6 joint industrial Stäubli TX-40 robot.

2. USUAL DYNAMIC IDENTIFICATION METHOD

2.1 *Inverse Dynamic Identification Model (IDIM)*

It is known that the dynamic model of any manipulator can be linearly written in term of a $(n \times 1)$ vector of standard parameters χ_{st} (Hollerbach *et al.* 2008), (Khalil and Dombre 2002). The modified Denavit and Hartenberg notation allows obtaining a dynamic model that is linear in relation to a set of standard dynamic parameters, χ_{st} :

$$\tau_{idm}(q,\dot{q},\ddot{q},\chi_{st}) = \Phi_{st}(q,\dot{q},\ddot{q})\chi_{st} \quad (1)$$

where:

τ_{idm} is the $(n \times 1)$ vector of the input efforts

Φ_{st} is the $(n \times n_{st})$ jacobian matrix of τ_{idm}, with respect to the $(n_{st} \times 1)$ vector χ_{st} of the standard parameters given by $\chi_{st} = \left[\chi_{st}^{1\,T}\ \chi_{st}^{2\,T}\ \ldots\ \chi_{st}^{n\,T}\right]^T$

$q,\dot{q},\ddot{q}$ are the vectors of the joint positions, velocities and accelerations, respectively.

For rigid robots, there are 14 standard parameters by link and joint. For the joint and link j, these parameters can be regrouped into the (14×1) vector χ_{st}^j (Khalil and Dombre 2002):

$$\chi_{st}^j = \left[XX_j\ XY_j\ XZ_j\ YY_j\ YZ_j\ ZZ_j\ MX_j\ MY_j\ MZ_j\ M_j\ Ia_j\ Fv_j\ Fc_j\ \tau_{off_j}\right]^T \quad (2)$$

where:

XX_j, XY_j, XZ_j, YY_j, YZ_j, ZZ_j are the 6 components of the inertia matrix of link j at the origin of frame j.

MX_j, MY_j, MZ_j are the 3 components of the first moment of link j, M_j is the mass of link j, Ia_j is a total inertia moment for rotor and gears of actuator j.

Fv_j, Fc_j are the visquous and Coulomb friction coefficients of the transmission chain, respectively,

$\tau_{off_j} = \tau_{offFS_j} + \tau_{off\tau_j}$ is an offset parameter which regroups the amplifier offset $\tau_{off\tau_j}$ and the asymmetrical Coulomb friction coefficient τ_{offFS_j}.

The identifiable parameters are the base parameters which are the minimum number of dynamic parameters from which the dynamic model can be calculated. They are obtained from the standard inertial parameters by regrouping some of them by means of linear relations (Mayeda *et al.* 1990), which can be determined for the serial robots using simple closed-form rules (Gautier and Khalil 1990), (Khalil and Dombre 2002), or by numerical method based on the QR decomposition (Gautier 1991).

The minimal dynamic model can be written using the n_b base dynamic parameters χ as follows:

$$\tau_{idm} = \Phi(q,\dot{q},\ddot{q})\chi \quad (3)$$

where Φ is obtained from Φ_{st} by eliminating the columns corresponding to the non identifiable parameters.

Because of perturbations due to noise measurement and modelling errors, the actual force/torque τ differs from τ_{idm} by an error, e, such that:

$$\tau = \tau_{idm} + e = \Phi(q,\dot{q},\ddot{q})\chi + e \quad (4)$$

$$\text{where } \tau = v_\tau\, g_\tau = \begin{bmatrix} v_\tau^1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & v_\tau^n \end{bmatrix} \begin{bmatrix} g_\tau^1 \\ \vdots \\ g_\tau^n \end{bmatrix} \quad (5)$$

v_τ is the $(n \times n)$ matrix of the actual current references of the current amplifiers (v_τ^j corresponds to actuator *j*) and g_τ is the $(n \times 1)$ vector of the joint drive gains (g_τ^j corresponds to actuator j). Equation (4) represents the IDIM.

2.2 Least Squares Identification of the Dynamic Parameters (IDIM-LS)

The off-line identification of the base dynamic parameters χ is considered, given measured or estimated off-line data for τ and $(q,\ \dot{q},\ \ddot{q})$, collected while the robot is tracking some planned trajectories. The model (4) is sampled and low pass filtered in order to get an over-determined linear system of $(n \times r)$ equations and n_b unknowns:

$$Y(\tau) = W\left(\hat{q},\hat{\dot{q}},\hat{\ddot{q}}\right)\chi + \rho \quad (6)$$

where

$(\hat{q},\ \hat{\dot{q}},\ \hat{\ddot{q}})$ are an estimation of $(q,\ \dot{q},\ \ddot{q})$, obtained by band-pass filtering and sampling the measure of *q* (Gautier 1997),

ρ is the $(r \times 1)$ vector of errors,

$W\left(\hat{q},\ \hat{\dot{q}},\ \hat{\ddot{q}}\right)$ is the $(r \times n_b)$ observation matrix.

Using the base parameters and tracking "exciting" reference trajectories, a well conditioned matrix W is obtained. The LS solution $\hat{\chi}$ of (6) is given by:

$$\hat{\chi} = \left(\left(W^T W\right)^{-1} W^T\right)Y = W^+ Y \quad (7)$$

It is computed using the QR factorization of W.

Standard deviations $\sigma_{\hat{\chi}_i}$, are estimated assuming that W is a deterministic matrix and ρ, is a zero-mean additive independent Gaussian noise, with a covariance matrix $C_{\rho\rho}$, such that:

$$C_{\rho\rho} = E(\rho\rho^{\mathrm{T}}) = \sigma_\rho^2 I_r \quad (8)$$

E is the expectation operator and I_r, the $(r \times r)$ identity matrix. An unbiased estimation of the standard deviation σ_ρ is:

$$\hat{\sigma}_\rho^2 = \left\|Y - W\hat{\chi}\right\|^2 / (r - b) \quad (9)$$

The covariance matrix of the estimation error is given by: $C_{\hat{\chi}\hat{\chi}} = E[(\chi - \hat{\chi})(\chi - \hat{\chi})^{\mathrm{T}}] = \hat{\sigma}_\rho^2 (W^{\mathrm{T}} W)^{-1}$.

$\sigma_{\hat{\chi}_i}^2 = C_{\hat{\chi}\hat{\chi}}(i,i)$ is the i^{th} diagonal coefficient of $C_{\hat{\chi}\hat{\chi}}$ (10)

The relative standard deviation $\%\sigma_{\hat{\chi}_{ri}}$ is given by:

$$\%\sigma_{\hat{\chi}_{ri}} = 100\sigma_{\hat{\chi}_i} / |\hat{\chi}_i| \text{, for } |\hat{\chi}_i| \neq 0 \quad (11)$$

The ordinary LS can be improved by taking into account different standard deviations on joint j equations errors (Gautier 1997). Data in Y and W of (6) are sorted and weighted with the inverse of the standard deviation of the error calculated from OLS solution of the equations of joint j (Gautier 1997).

This weighting operation normalises the errors in (6) and gives the weighted LS estimation of the parameters (IDIM-WLS).

3. GLOBAL IDENTIFICATION OF THE JOINT DRIVE GAINS

3.1 IDIM Including a Payload and Drive Gains

The payload is considered as a link $n+1$ fixed to the link n of the robot. Only n_{kL} of its parameters are considered known. The model (4) becomes:

$$\tau = v_\tau g_\tau = \begin{bmatrix} \Phi & \Phi_{uL} & \Phi_{kL} \end{bmatrix} \begin{bmatrix} \chi^T & \chi_{uL}^T & \chi_{kL}^T \end{bmatrix}^T + e \quad (12)$$

where:

χ_{kL} is the $(n_{kL} \times 1)$ vector of inertial parameters of the payload which are estimated with a CAD software or measured with a balance,

χ_{uL} is the $((10 - n_{kL}) \times 1)$ vector of the unknown inertial parameters of the payload,

Φ_{kL} is the $(n \times n_{kL})$ jacobian matrix of τ_{idm}, with respect to the vector χ_{kL},

Φ_{uL} is the $(n \times (10 - n_{kL}))$ jacobian matrix of τ_{idm}, with respect to the vector χ_{uL}.

3.2 Weighted Total Least Squares Identification of the Drive Gains (IDIM-WTLS)

Details on the Total LS (TLS) identification method can be found in (Van Huffel and Vandewalle 1991) and many papers of the same authors. This method has been applied in (Gautier *et al.* 1994) for the identification of the drive gains and the dynamic parameters on a two degrees of freedom robot (dof) but gives arguable results due to the lack of an accurate scale factor. In this paper three major improvements are proposed:

- the accurate scaling of parameters using the precise weighed value of an additional payload mass;
- a weighting procedure of rows and columns of the observation matrix taking into account an *a priori* confidence on the measures.
- an experimental validation on a 6 dof industrial robot which shows the efficiency of these approaches.

In order to identify the payload parameters, it is necessary that the robot carried out two trajectories: (a) without the payload and (b) with the payload fixed to the end-effector (Khalil *et al.* 2007). The sampling and filtering of the model IDIM (12) can be then written as:

$$Y = \begin{bmatrix} V_{\tau a} \\ V_{\tau b} \end{bmatrix} g_\tau = \begin{bmatrix} W_a & 0 & 0 \\ W_b & W_{uL} & W_{kL} \end{bmatrix} \begin{bmatrix} \chi^T & \chi_{uL}^T & \chi_{kL}^T \end{bmatrix}^T + \rho \quad (13)$$

where:

$V_{\tau a}$ is the matrix of v_τ samples in the unloaded case,

$V_{\tau b}$ is the matrix of v_τ samples in the loaded case,

$$V_{\tau i} = \begin{bmatrix} V_{\tau i}^1 & 0 & \cdots & 0 \\ 0 & V_{\tau i}^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & V_{\tau i}^n \end{bmatrix}, \quad V_{\tau i}^j = \begin{bmatrix} v_{\tau i,1}^j \\ v_{\tau i,2}^j \\ \vdots \\ v_{\tau i,r/n}^j \end{bmatrix}, \text{ with } i = a, b \quad (14)$$

$v_{\tau i,k}^j$ is the *k*-th sample of current reference for actuator *j*,

W_a is the observation matrix of the robot in the unloaded case,

W_b is the observation matrix of the robot in the loaded case,

W_{uL} is the observation matrix of the robot corresponding to the unknown payload inertial parameters,

W_{kL} is the observation matrix of the robot corresponding to the known payload inertial parameters. Eq. (13) becomes:

$$W_{tot} \chi_{tot} = \rho , \quad (15)$$

where

$W_{tot} = \begin{bmatrix} -W_a & V_a & 0 & 0 \\ -W_b & V_b & -W_{uL} & -W_{kL}\chi_{kL} \end{bmatrix}$ is a $r \times (n_b + n + 11 - n_{kL})$ matrix,

and $\chi_{tot} = \begin{bmatrix} \chi^T & g_\tau^T & \chi_{uL}^T & \delta \end{bmatrix}^T$ is a $(n_b + n + 11 - n_{kL})$ vector and δ is a scalar which should be equal to 1.

Without perturbation, $\rho = 0$ and W_{tot} should be rank deficient to get the solutions $\lambda \chi_{tot} \neq 0$ depending on a scale coefficient λ. However because of the measurement perturbations, W_{tot} is a full rank matrix. Therefore, the system (15) is replaced by the compatible system closest to (15) with respect to the Frobenius norm:

$$\hat{W}_{tot} \hat{\chi}_{tot} = 0 , \quad (16)$$

where $\hat{W}_{tot}$ is the rank deficient matrix, with the same dimension as W_{tot}, which minimizes the Frobenius norm $\left\| W_{tot} - \hat{W}_{tot} \right\|_F$,

$\hat{\chi}_{tot} = \begin{bmatrix} \hat{\chi}^T & \hat{g}_\tau^T & \hat{\chi}_{uL}^T & \hat{\delta} \end{bmatrix}^T$ is the solution of the compatible system closest to (15).

$\hat{W}_{tot}$ can be computed thanks to the Singular Value Decomposition (SVD) of W_{tot} (Golub and Van Loan 1996):

$$W_{tot} = U \begin{bmatrix} diag(s_i) \\ 0 \end{bmatrix} V^T , \quad (17)$$

where U and V are $(r\times r)$ and $(n_b+n+11-n_{kL})\times(n_b+n+11-n_{kL})$ orthonormal matrices, respectively, and $diag(s_i)$ is a $((n_b+n+11-n_{kL})\times(n_b+n+11-n_{kL}))$ diagonal matrix with singular values s_i of W_{tot} sorted in decreasing order. The solution of (16) is given by:

$$\hat{W}_{tot}=W_{tot}-s_{n+n_b+11-n_{kL}}U_{n+n_b+11-n_{kL}}V^T_{n+n_b+11-n_{kL}}, \qquad (18)$$

where $s_{n+n_b+11-n_{kL}}$ is the smallest singular value of W_{tot} and $U_{n+n_b+11-n_{kL}}$ ($V_{n+n_b+11-n_{kL}}$, resp.) the column of U (V, resp.) corresponding to $s_{n+n_b+11-n_{kL}}$. Then, the normalized optimal solution $\hat{\chi}^n_{tot}$ ($\|\hat{\chi}^n_{tot}\|=1$) is given by the last column of V, $\hat{\chi}^n_{tot}=V_{n+n_b+11-n_{kL}}$ (Gautier *et al.* 1994).

There are infinity of vectors $\hat{\chi}_{tot}=\lambda\hat{\chi}^n_{tot}$ that can be obtained by a scale factor λ. A unique solution $\hat{\chi}^*_{tot}=\hat{\lambda}\hat{\chi}^n_{tot}$ can be found by taking into account that the last value of $\hat{\chi}^*_{tot}$ should be equal to 1, i.e. $\hat{\lambda}=1/\hat{\delta}$.

In order to improve the estimation of $\hat{\chi}^*_{tot}$, the rows and columns of W_{tot} are weighted taking into account the confidence on the measures. Two types of weighting factors are used:

1. As proposed in IDIM-WLS (Gautier 1997) (section 2.2), to improve the ordinary LS, each row corresponding to joint j equation is weighted by the inverse of $\hat{\sigma}^j_\rho$;
2. It is also proposed to weight the columns of the observation matrix in order to take into account the *a priori* relative confidence between the columns. Indeed, as explained in section 2.2, the coefficients of matrices W_a, W_b, W_{uL} and W_{kL} are calculated with the values of $(\hat{q},\ \hat{\dot{q}},\ \hat{\ddot{q}})$ estimated by band-pass filtering and sampling the measure of q. Therefore, the coefficients of these columns are considered less accurate than $V_{\tau a}$ and $V_{\tau b}$ obtained with the direct measures of v_τ. In order to increase the confidence on these columns, $V_{\tau a}$ and $V_{\tau b}$ are weighted by a factor α and the new system becomes:

$$W^w_{tot}\chi^w_{tot}=\rho \qquad (19)$$

where

$$W^w_{tot}=\begin{bmatrix}-W_a & \alpha V_a & 0 & 0\\ -W_b & \alpha V_b & -W_{uL} & -W_{kL}\chi_{kL}\end{bmatrix},$$

and $\chi^w_{tot}=\begin{bmatrix}\chi^T & g^T_\tau/\alpha & \chi^T_{uL} & \delta\end{bmatrix}^T$.

3.3 Discussion on the A Priori Knowledge of the Payload Parameters and on the Choice of the Weighting Factors

The accuracy of $\hat{\lambda}$ depends on the accuracy of χ_{kL}, depending on the knowledge of the payload parameters.

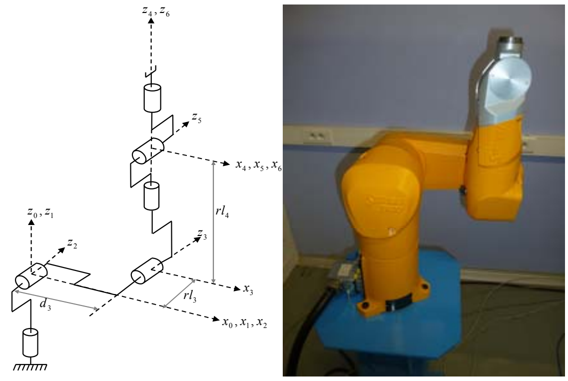

Fig. 1. Link frames of the TX-40 robot

Table 1.
Geometric parameters of the TX-40 robot with the payload

j	σ_j	α_j	d_j	θ_j	r_j
1	0	0	0	q_1	0
2	0	$-\pi/2$	0	$q_2-\pi/2$	0
3	0	0	d_3 = 0.225 m	$q_3+\pi/2$	rl_3 = 0.035 m
4	0	$+\pi/2$	0	q_4	rl_4 = 0.225 m
5	0	$-\pi/2$	0	q_5	0
6	0	$+\pi/2$	0	q_6	0
7	2	0	0	0	0

The most accurate payload parameter is the mass value M_L that can be accurately measured using a weighing machine.

The choice of $\hat{\sigma}^j_\rho$ to weight the rows of W^p_{tot} is physically meaningful but the choice of parameter α is not straightforward. In the remainder, it is proposed to minimize the relative norm of error $\|\rho(\alpha)\|=\|Y(\alpha)-W\hat{\chi}(\alpha)\|$ with respect to α. The value $\hat{\alpha}=5$ gives the best results which are presented in the following section.

4. CASE STUDY

4.1 Description of the TX-40 Kinematics

The Stäubli TX-40 robot (Fig. 1) has a serial structure with six rotational joints. Its kinematics is defined using the modified Denavit and Hartenberg notation (MDH) (Khalil and Dombre 2002). In this notation, the link j fixed frame is defined such that the z_j axis is taken along joint j axis and the x_j axis is along the common normal between z_j and z_{j+1} (Fig. 1). The geometric parameters defining the robot frames are given in Table 1. The payload is denoted as the link 7. The parameter $\sigma_j=0$, means that joint j is rotational, α_j and d_j parameterize the angle and distance between z_{j-1} and z_j along x_{j-1}, respectively, whereas θ_j and r_j parameterize the angle and distance between x_{j-1} and x_j along z_j, respectively. For link 7, $\sigma_j=2$ means that the link 7 is fixed on the link 6. Since all the joints are rotational then θ_j is the joint position value q_j given by the CS8C controller of the TX-40 robot, except for joints 2 and 3 where the MDH notation differs the Staübli variables (Table 1):

$\theta_2 = q_2 - \pi/2$, $\theta_3 = q_3 + \pi/2$.

The TX40 robot is characterized by a coupling between the joints 5 and 6 such that:

$$\begin{bmatrix} \dot{q}r_5 \\ \dot{q}r_6 \end{bmatrix} = \begin{bmatrix} K5 & 0 \\ K6 & K6 \end{bmatrix} \begin{bmatrix} \dot{q}_5 \\ \dot{q}_6 \end{bmatrix}, \begin{bmatrix} \tau_{c_5} \\ \tau_{c_6} \end{bmatrix} = \begin{bmatrix} K5 & K6 \\ 0 & K6 \end{bmatrix} \begin{bmatrix} \tau_{r_5} \\ \tau_{r_6} \end{bmatrix} \quad (20)$$

where $\dot{q}r_j$ is the velocity of the rotor of motor j, $\dot{q}_j$ is the velocity of joint j, $K5$ is the transmission gain ratio of axis 5 and $K6$ is the transmission gain ratio of axis 6, τ_{cj} is the motor torque of joint j, taking into account the coupling effect, τ_{rj} is the electro-magnetic torque of the rotor of motor j. With the coupling between joints 5 and 6, (5) and (14) becomes:

$$\tau = \begin{bmatrix} v_\tau^1 & 0 & \cdots & 0 \\ 0 & \ddots & \cdots & 0 \\ \vdots & \vdots & v_\tau^5 & v_\tau^6 \\ 0 & 0 & 0 & v_\tau^6 \end{bmatrix} \begin{bmatrix} g_\tau^1 \\ \vdots \\ g_\tau^5 \\ g_\tau^6 \end{bmatrix}, \text{ and } V_{\tau i} = \begin{bmatrix} V_{\tau i}^1 & 0 & \cdots & 0 \\ 0 & \ddots & \cdots & 0 \\ \vdots & \vdots & V_{\tau i}^5 & V_{\tau i}^6 \\ 0 & 0 & 0 & V_{\tau i}^6 \end{bmatrix} \quad (21)$$

The coupling between joints 5 and 6 also adds the effect of the inertia of rotor 6 and new viscous and Coulomb friction parameters fv_{m6} and fc_{m6} , to both τ_{c5} and τ_{c6}.

We can write:

$$\tau_{c_5} = \tau_5 + Ia_6\,\ddot{q}_6 + fvm_6\,\dot{q}_6 + fcm_6\,\text{sign}(\dot{q}_6) \text{ and}$$

$$\tau_{c_6} = \tau_6 + Ia_6\,\ddot{q}_5 + fvm_6\,\dot{q}_5 + fcm_6\left(\text{sign}(\dot{q}_5 + \dot{q}_6) - \text{sign}(\dot{q}_6)\right) .$$

where τ_5, τ_6 already contain the terms $(Ia_j\ddot{q}_j + fv_j\dot{q}_j + fc_j sign(\dot{q}_j))$, for j=5 and 6 respectively,

$$Ia_5 = K_5^2 Ja_5 + K_6^2 Ja_6 \text{ and } Ia_6 = K_6^2 Ja_6 \quad (22)$$

Ja_j is the moment of inertia of rotor j .

The TX40 has N_s=86 standard dynamic parameters given by the 14×6 usual standard parameters, plus fv_{m6} and fc_{m6}.

4.2 Identification of the Drive Gains

The proposed method is validated using a calibrated payload (Fig. 2).

Its mass has been measured with a weighing machine (M_L = 4.59 Kg± 0.05 Kg). The other parameters have been calculated using CAD software. They are given in table 2. Their values are accurate due to the simplicity of the payload shape (Fig. 2).

Two different identifications of the payload inertia parameters are achieved:

- *Case 1:* the payload parameters are identified using the manufacturer's drive gains
- *Case 2:* the drive gains are first identified with the base parameters with IDIM-WTLS using the knowledge on the payload mass. They are then used in order to achieve a new identification of the new the payload parameters and the robot dynamic parameters with IDIM-WLS.

The manufacturer's drive gains (*Case 1*) and the identified ones (*Cases 2*) are given in table 3. For each joint, the identified values are close for the manufacturer's values, but the mean error is about 9%. The maximal error grows up to 24%!

Fig. 2. The 4.59 Kg payload

Table 2. Identification of the payload dynamic parameters.

Par.	*Nom. val.*	Case 1 Id.val.	$2\sigma_{\hat{\chi}_i}$	$\%\sigma_{\hat{\chi}_{ri}}$	Case 2 Id. val.	$2\sigma_{\hat{\chi}_i}$	$\%\sigma_{\hat{\chi}_{ri}}$
XX_L	*0.64e-1*	1.12e-1	1.99e-3	1.8	**8.14e-2**	1.54e-3	1.9
XY_L	*-1.80e-2*	-1.83e-2	7.21e-4	3.9	**-1.53e-2**	6.61e-4	4.3
XZ_L	*2.60e-2*	2.93e-2	8.88e-4	3.0	**2.87e-2**	5.87e-4	2.0
YY_L	*0.64e-1*	1.15e-1	1.80e-3	1.6	**8.71e-2**	1.41e-3	1.6
YZ_L	*2.60e-2*	4.15e-2	6.32e-4	1.5	**3.74e-2**	5.16e-4	1.4
ZZ_L	*4.40e-2*	7.02e-2	5.78e-4	0.8	**4.51e-2**	4.37e-4	1.0
MX_L	*-2.90e-1*	-3.02e-1	2.47e-3	0.8	**-2.73e-1**	2.05e-3	0.8
MY_L	*-2.90e-1*	-3.20e-1	2.55e-3	0.8	**-2.85e-1**	2.11e-3	0.7
MZ_L	*4.10e-1*	5.18e-1	4.38e-3	0.8	**4.44e-1**	3.43e-3	0.8
M_L	*4.59*	4.48	3.02e-2	0.7	**4.57**	2.76e-2	0.6

$\sigma_{\hat{\chi}_i}$ is the standard deviation and $\%\sigma_{\hat{\chi}_{ri}}$ its relative value

Table 3. Identified drive gains.

		Joint 1	Joint 2	Joint 3	Joint 4	Joint 5	Joint 6
A priori val.	g_τ^j	*32.96*	*32.96*	*25.65*	*-11.52*	*18.48*	*7.68*
Case 2	g_τ^j	**33.7**	**32.2**	**24.1**	**-8.80**	**16.50**	**6.82**
	$2\sigma_{\hat{\chi}_i}$	0.04	0.03	0.03	0.02	0.03	0.01
	$\%\sigma_{\hat{\chi}_{ri}}$	0.61	0.45	0.60	0.83	0.77	0.78

Table 4. Quality of identification.

	Error norm $\lVert\hat{\rho}\rVert$	Relative Error norm $\lVert\hat{\rho}\rVert / \lVert Y\rVert$	$\hat{\sigma}_\rho$
Case 1	33.8366	0.043245	0.495164
Case 2	**31.9702**	**0.0409025**	**0.4667879**

$\lVert\hat{\rho}\rVert = \lVert Y - W\hat{\chi}\rVert$ is the minimal norm of error.

The identified values of the payload inertial parameters are presented in table 2. Moreover, the quality of identification is detailed at table 4. It appears that the identified gains lead to the best results. The efficiency and the simplicity of the method are really appealing, especially for industrial robots for which manufacturer's gains are too often very difficult to obtain.

Finally, in order to validate the new drive gain values a new payload is identified (Table 5). The parameters are very close to the *a priori* ones in all cases. The torques calculated with the model (12) identified with the gains of Case 2 are presented in Fig. 3. It is possible to conclude that the drive gains have been well identified with the IDIM-WTLS.

5. CONCLUSION

This paper has presented a new method for the global identification of the total drive gains for robot joints. This method is easy to implement and does not need any special test or measurement on elements inside the joint drive train. It

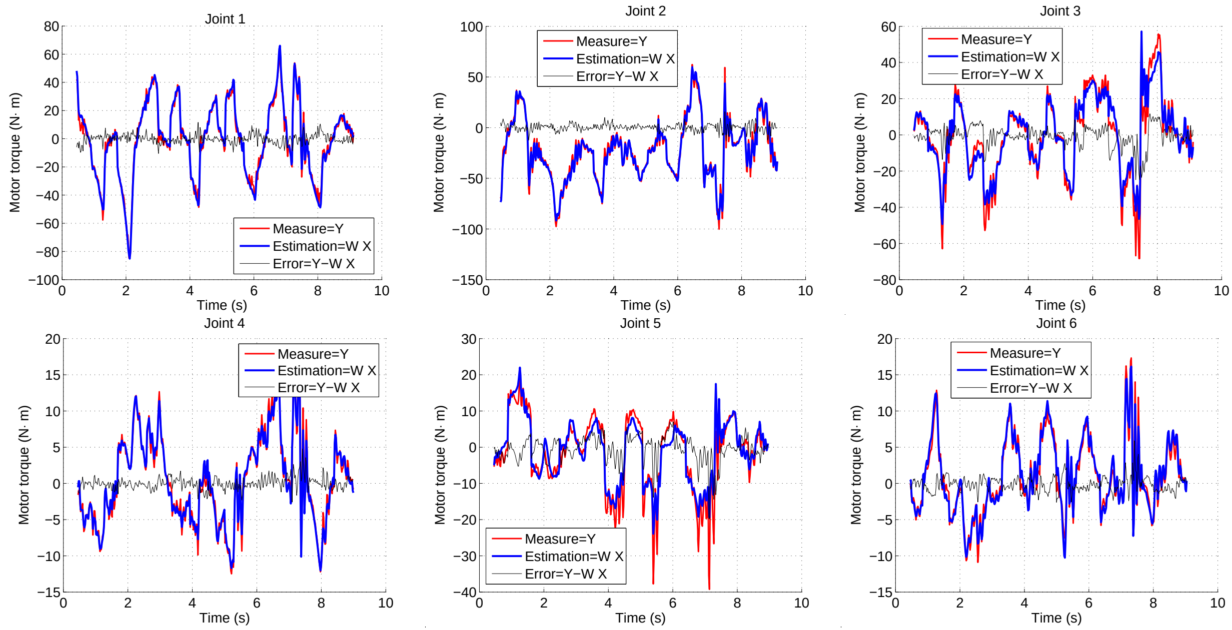

Fig. 3. Measured and computed torques of the TX-40 with the payload of 4.59 kg.

Table 5.
Identification of the new payload dynamic parameters.

		Case 1			Case 2		
Par.	*Nom. val.*	Id.val.	$2\sigma_{\hat{\chi}_i}$	$\%\sigma_{\hat{\chi}_n}$	Id. val.	$2\sigma_{\hat{\chi}_i}$	$\%\sigma_{\hat{\chi}_n}$
XX_L	*1.51e-2*	1.57e-2	8.75e-4	5.6	1.11e-2	8.07e-4	7.2
XY_L	*-9.06e-4*	-2.41e-3	3.16e-4	13.1	-2.08e-3	2.79e-4	13.4
XZ_L	*3.61e-3*	4.21e-3	3.34e-4	7.9	4.11e-3	2.94e-4	7.1
YY_L	*1.51e-2*	1.40e-2	8.95e-4	6.4	1.13e-2	7.57e-4	6.7
YZ_L	*3.61e-3*	1.93e-3	3.00e-4	15.5	1.49e-3	2.66e-4	17.9
ZZ_L	*3.44e-3*	3.88e-3	2.88e-4	7.4	1.34e-3	2.88e-4	21.5
MX_L	*-4.00e-2*	-2.37e-2	1.59e-3	4.7	-2.74e-2	1.30e-3	4.8
MY_L	*-3.99e-2*	-4.18e-2	1.41e-3	3.4	-3.90e-2	1.31e-3	3.3
MZ_L	*0.15*	0.192	2.51e-3	1.3	0.166	2.22e-3	1.3
M_L	*1.686*	1.66	1.74e-2	1.0	1.66	1.73e-2	1.0

$\sigma_{\hat{\chi}_i}$ is the standard deviation and $\%\sigma_{\hat{\chi}_n}$ its relative value

is based on a IDIM-WTLS technique using current reference and position sampled data while the robot is tracking one reference trajectory without load fixed on the robot and one trajectory with a known payload fixed on the robot, whose inertial parameters are measured. The method has been experimentally validated on an industrial Stäubli TX-40 robot. Using the identified drive gains, the identification of the total dynamic model has been improved and another payload has been accurately identified. This shows the effectiveness of the method.

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