Global Identification of Drive Gains Parameters of Robots Using a Known Payload

Maxime Gautier and Sébastien Briot

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 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 Stäubli TX-40 robot.**

I. Introduction

SEVERAL schemes have been proposed in the literature to identify the dynamic parameters of robots [1]–[7]. Most of the dynamic identification methods have the following common 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 [8].

This needs to calibrate the drive train constituted by a current 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 [8][9].

Several papers on the topic of the joint drive gains identification have been published in the past [8]–[11], but all of them propose to identify each gain separately. This does not allow taking into account the dynamic coupling between the robot axes.

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 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. Contrary to the previous works, all drive gains are calculated in the same solving loop by the total LS solution of an over-determined system in order to take into account the coupling between the robot axes.

The method is experimentally validated on an industrial Stäubli TX-40 robot.

The paper is organized as follows: section 2 recalls the dynamic modelling and identification procedures. Section 3 deals with the new modelling and identification method for the robot drive gains parameters. Section 4 presents the experimental validations. Finally, section 5 gives the conclusion.

II. Usual Inverse Dynamic Models and Identification

A. *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

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M. Gautier is with the University of Nantes and the Institut de Recherche en Communications et Cybernétique de Nantes (IRCCyN) 44321 Nantes France (phone: +33240376960; fax: +33240376930; e-mail: Maxime.Gautier@irccyn.ec-nantes.fr).

S. Briot is with the CNRS and IRCCyN, 44321 Nantes France (e-mail: Sebastien.Briot@irccyn.ec-nantes.fr).

parameters χ_{st} [2], [4], [5], [11]. 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 $\chi_{st} = \left[\chi_{st}^{1\,T}\ \chi_{st}^{2\,T}\ \dots\ \chi_{st}^{n\,T}\right]^T$

$q,\dot{q},\ddot{q}$ 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} [5]:

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

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 [15], which can be determined for the serial robots using simple closed-form rules [3], [5], or by numerical method based on the QR decomposition [14].

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:

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

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.

B. 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:

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

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 [16].

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

$W(\hat{q},\ \hat{\dot{q}},\ \hat{\ddot{q}})$ 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 [16]. 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 [16].

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

III. Global Identification of the Joint Drive Gains

A. 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_L 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 $(n_L \times 1)$ vector of the known inertial parameters of the payload;

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

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

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

B. Total Least Squares Identification of the Drive Gains (IDIM-TLS)

Details on the TLS identification method can be found in [19] and many papers of the same authors. This method has been applied in [18] 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 we propose a major improvement with the scaling of parameters using the accurate value of an additional payload mass.

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 [17]. 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

$W_{tot} = \begin{bmatrix} -W_a & V_a & 0 & 0 \\ -W_b & V_b & -W_{uL} & -W_{kL} \end{bmatrix}$ is a $(r_{tot}\times r_{tot})$ matrix,

and $\chi_{tot} = \begin{bmatrix} \chi^T & g_\tau^T & \chi_{uL}^T & \chi_{kL}^T \end{bmatrix}^T$ is a (n_b+n+10) vector.

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:

$$\hat{W}_{tot}\hat{\chi}_{tot} = 0, \ \hat{\chi}_{tot} = \begin{bmatrix} \hat{\chi}^T, \hat{g}_\tau^T, \hat{\chi}_{uL}^T, \hat{\chi}_{kL}^T \end{bmatrix}^T \quad (16)$$

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

$\hat{\chi}_{tot}$ 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} [20]:

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

where U and V are $(r_{tot}\times r_{tot})$ and $((n_b+n+10)\times(n_b+n+10))$ orthonormal matrices, respectively, and $diag(\sigma_i)$ is a $((n_b+n+10)\times(n_b+n+10))$ diagonal matrix with singular values σ_i of W_{tot} sorted in decreasing order. The solution of (16) is given by:

$$\hat{W}_{tot} = W_{tot} - \sigma_{n+n_b} U_{n+n_b} V_{n+n_b}^T, \quad (18)$$

where σ_{n+n_b} is the smallest singular value of W_{tot} and U_{n+n_b} (V_{n+n_b}, resp.) the column of U (V, resp.) corresponding to σ_{n+n_b}. Then, the normalized optimal solution $\hat{\chi}_{tot}^1$ ($\left\|\hat{\chi}_{tot}^1\right\| = 1$) is given by the last column of V, $\hat{\chi}_{tot}^1 = V_{n+n_b}$ [18].

There are infinity of vectors $\hat{\chi}_{tot} = \lambda\hat{\chi}_{tot}^1$ that can be obtained by a scale factor λ. A unique solution $\hat{\chi}_{tot}^* = \hat{\lambda}\hat{\chi}_{tot}^1$ can be found by taking into account the known values χ_{kL} of the payload parameters and their corresponding identified values $\hat{\chi}_{kL}^1$. The optimal scale factor $\hat{\lambda}$ can be calculated as the LS solution of :

$$\chi_{kL} = \hat{\chi}_{kL}^1 \lambda + \rho_{kL} \quad (19)$$

C. *Discussion on the A Priori Knowledge of the Payload Parameters*

The accuracy of $\hat{\lambda}$ depends on the accuracy of χ_{kL}, depending on the knowledge of the payload parameters, and on the accuracy of $\hat{\chi}_{kL}^{I}$ in (19).

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

Then in the next section we shall compare 2 solutions:

$$\hat{\lambda}_1 = \hat{\chi}_{kL}^{I\,+}\chi_{kL} \tag{20}$$

where $\hat{\lambda}_1$ is the LS solution of (19) calculated with all known payload parameters, and:

$$\hat{\lambda}_2 = M_L \big/ \hat{M}_L^{I} \tag{21}$$

where $\hat{M}_L^{I}$ is the identified value of M_L in $\hat{\chi}_{tot}^{I}$.

It will be shown in the next section, that the experimental results confirm the efficiency of the approach that uses the mass only.

IV. Case Study

A. *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) [12]. 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 the MDH position θ_j is equal to the joint position 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, $\theta_2 = q_2 - \pi/2$, $\theta_3 = q_3 + \pi/2$.

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

$$\begin{bmatrix}\dot{q}r_5\\ \dot{q}r_6\end{bmatrix} = \begin{bmatrix}K5 & 0\\ K6 & K6\end{bmatrix}\begin{bmatrix}\dot{q}_5\\ \dot{q}_6\end{bmatrix},\quad \begin{bmatrix}\tau_{c_5}\\ \tau_{c_6}\end{bmatrix} = \begin{bmatrix}K5 & K6\\ 0 & K6\end{bmatrix}\begin{bmatrix}\tau_{r_5}\\ \tau_{r_6}\end{bmatrix} \tag{22}$$

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

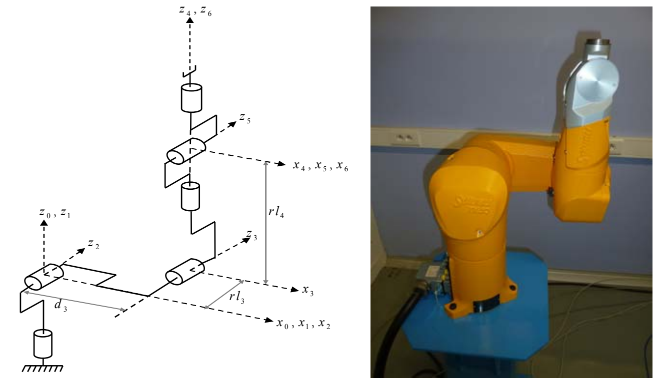

Fig. 1. Link frames of the TX-40 robot

TABLE I
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

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:

$$\tau = v_\tau\, g_\tau = \begin{bmatrix} v_\tau^1 & 0 & \cdots & 0\\ 0 & \ddots & \cdots & 0\\ \vdots & \vdots & v_\tau^5 & v_\tau^6\\ 0 & 0 & 0 & v_\tau^6\end{bmatrix}\begin{bmatrix} g_\tau^1\\ \vdots\\ g_\tau^5\\ g_\tau^6\end{bmatrix}, \tag{23}$$

$$\text{and } V_{\tau i} = \begin{bmatrix} V_{\tau i}^1 & 0 & \cdots & 0\\ 0 & \ddots & \cdots & 0\\ \vdots & \vdots & V_{\tau i}^5 & V_{\tau i}^6\\ 0 & 0 & 0 & V_{\tau i}^6\end{bmatrix} \tag{24}$$

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:

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

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

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,

$$Ia_5 = K_5^2 Ja_5 + K_6^2 Ja_6 \text{ and } Ia_6 = K_6^2 Ja_6 \tag{25}$$

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}.

B. *Identification of the Drive Gains*

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

Fig. 2. The 4.59 Kg payload

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).

Three 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-TLS using (20) calculated with all known payload parameters. They are then used in order to reidentifiy the payload parameters and the robot dynamic parameters with IDIM-WLS.
- *Case 3:* the drive gains are first identified with the base parameters with IDIM-TLS using (21) calculated with only the mass of the payload. They are then used in order to reidentifiy the payload parameters and the robot dynamic parameters with IDIM-WLS.

The a priori drive gains (*Case 1*) and the identified ones (*Cases 2 and 3*) are given in table 3. For each joints, the identified values are close for the manufacturer's values, but the mean error is about 11%. The maximal error grows up to 21%!

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. Moreover, the best model identification is achieved with the use of the TLS with only the mass. This result is really appealing for industrial applications and show the efficiency and the simplicity of the method.

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	35.22	32.02	23.92	-9.05	15.49	6.55
	$2\sigma_{\hat{\chi}_i}$	0.540	0.483	0.372	0.015	0.252	0.011
	$\%\sigma_{\hat{\chi}_{ri}}$	1.53	1.51	1.56	1.67	1.63	1.63
Case 3	g_τ^j	**35.24**	**32.04**	**23.94**	**-9.05**	**15.50**	**6.56**
	$2\sigma_{\hat{\chi}_i}$	0.540	0.484	0.372	0.015	0.252	0.011
	$\%\sigma_{\hat{\chi}_{ri}}$	1.53	1.51	1.56	1.67	1.63	1.64

TABLE 4
QUALITY OF IDENTIFICATION.

	Error norm $\|\hat{\rho}\|$	Relative Error norm $\|\hat{\rho}\|/\|Y\|$	$\hat{\sigma}_\rho$
Case 1	33.8366	0.043245	0.495164
Case 2	31.6252	0.0403937	0.462829
Case 3	**31.4783**	**0.0402846**	**0.46068**

$\|\hat{\rho}\| = \|Y - W\hat{\chi}\|$ is the minimal norm of error, $\hat{\sigma}_\rho$ is given by (9).

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 but the best identification is still obtained with the gains of Case 3. The torques calculated with the model (12) identified with the gains of Case 3 are presented in Fig. 3. It is possible to conclude that the drive gains have been well identified with the IDIM-TLS.

V. 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 is based on a IDIM-TLS 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 or calculated by a CAD model. 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

TABLE 2
IDENTIFICATION OF THE PAYLOAD DYNAMIC PARAMETERS.

		Case 1			Case 2			Case 3		
Parameter	*A priori value*	Identified values	$2\sigma_{\hat{\chi}_i}$	$\%\sigma_{\hat{\chi}_{ri}}$	Identified values	$2\sigma_{\hat{\chi}_i}$	$\%\sigma_{\hat{\chi}_{ri}}$	Identified values	$2\sigma_{\hat{\chi}_i}$	$\%\sigma_{\hat{\chi}_{ri}}$
XX_L	*0.64e-1*	1.12e-1	1.99e-3	1.8	9.02e-2	1.54e-3	1.7	**9.24e-2**	1.45e-3	1.6
XY_L	*-1.80e-2*	-1.83e-2	7.21e-4	3.9	-1.34e-2	6.65e-4	5.0	**-1.45e-2**	6.75e-4	4.7
XZ_L	*2.60e-2*	2.93e-2	8.88e-4	3.0	1.96e-2	5.91e-4	3.0	**1.93e-2**	5.90e-4	3.1
YY_L	*0.64e-1*	1.15e-1	1.80e-3	1.6	9.12e-2	1.41e-3	1.5	**8.77e-2**	1.44e-3	1.6
YZ_L	*2.60e-2*	4.15e-2	6.32e-4	1.5	3.59e-2	4.93e-4	1.4	**3.75e-2**	6.45e-4	1.7
ZZ_L	*4.40e-2*	7.02e-2	5.78e-4	0.8	6.00e-2	4.68e-4	0.8	**6.01e-2**	4.69e-4	0.8
MX_L	*-2.90e-1*	-3.02e-1	2.47e-3	0.8	-2.82e-1	2.35e-3	0.8	**-2.83e-1**	2.35e-3	0.8
MY_L	*-2.90e-1*	-3.20e-1	2.55e-3	0.8	-2.82e-1	1.84e-3	0.7	**-2.81e-1**	1.83e-3	0.7
MZ_L	*4.10e-1*	5.18e-1	4.38e-3	0.8	4.42e-1	3.41e-3	0.8	**4.44e-1**	3.39e-3	0.8
M_L	*4.59*	4.48	3.02e-2	0.7	4.58	2.73e-2	0.6	**4.58**	2.72e-2	0.6

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

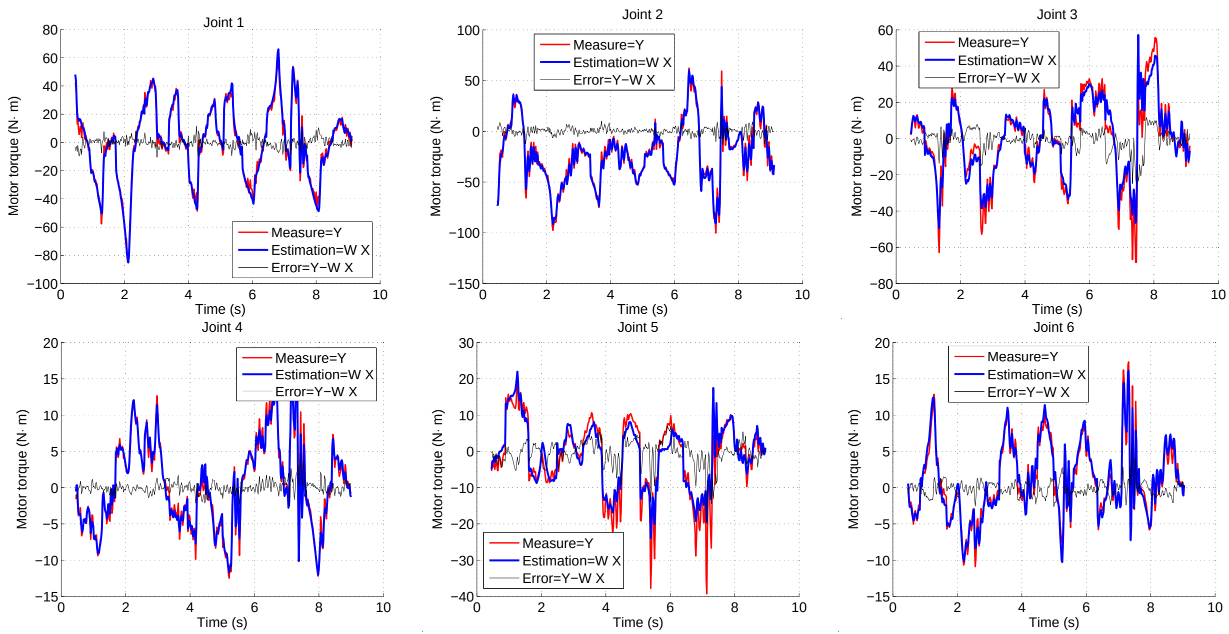

Fig. 3. Measured and reconstructed torques of the TX-40.

TABLE 5
IDENTIFICATION OF THE NEW PAYLOAD DYNAMIC PARAMETERS.

Parameter	*A priori value*	Case 1 Identified values	Case 1 $2\sigma_{\hat{\chi}_i}$	Case 1 $\%\sigma_{\hat{\chi}_n}$	Case 2 Identified values	Case 2 $2\sigma_{\hat{\chi}_i}$	Case 2 $\%\sigma_{\hat{\chi}_n}$	Case 3 Identified values	Case 3 $2\sigma_{\hat{\chi}_i}$	Case 3 $\%\sigma_{\hat{\chi}_n}$
XX_L	*1.51e-2*	1.57e-2	8.75e-4	5.6	1.35e-2	7.64e-4	5.7	**1.15e-2**	8.29e-4	7.2
XY_L	*-9.06e-4*	-2.41e-3	3.16e-4	13.1	-1.60e-3	3.47e-4	21.7	**-1.71e-3**	3.52e-4	20.6
XZ_L	*3.61e-3*	4.21e-3	3.34e-4	7.9	4.04e-3	2.91e-4	7.2	**3.95e-3**	3.84e-4	9.7
YY_L	*1.51e-2*	1.40e-2	8.95e-4	6.4	1.24e-2	7.78e-4	6.3	**1.06e-2**	7.71e-4	7.3
YZ_L	*3.61e-3*	1.93e-3	3.00e-4	15.5	1.05e-3	2.63e-4	25.1	**1.59e-3**	2.63e-4	16.5
ZZ_L	*3.44e-3*	3.88e-3	2.88e-4	7.4	1.26e-3	2.85e-4	22.7	**3.26e-3**	2.55e-4	7.8
MX_L	*-4.00e-2*	-2.37e-2	1.59e-3	4.7	-2.58e-2	1.29e-3	5.0	**-2.73e-2**	1.31e-3	4.8
MY_L	*-3.99e-2*	-4.18e-2	1.41e-3	3.4	-3.52e-2	1.17e-3	3.3	**-3.49e-2**	1.18e-3	3.4
MZ_L	*0.15*	0.192	2.51e-3	1.3	0.161	2.24e-3	1.4	**0.161**	2.26e-3	1.4
M_L	*1.686*	1.66	1.74e-2	1.0	1.67	1.74e-2	1.0	**1.68**	1.76e-2	1.0

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

identified. This shows the effectiveness of the method.

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