

# In situ calibration of joint torque sensors of the KUKA LightWeight Robot using only internal controller data

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**Abstract**— The Kuka LWR is equipped with torque sensors mounted into the actuated joints. Each torque sensor is calibrated separately before it is mounted on the robot. This needs a second calibration at the last stage of the assembling of the robot in order to take into account the effect of the robot structure through its jacobian matrix. This final calibration is necessary to improve the accuracy of the estimation of the interaction wrench of the robot with its environment. However, the proposed calibration techniques are usually complicated, time-consuming, and must be carried out before assembling the sensors on the robot. In this paper, a simple and fast method for calibrating the sensors once they are assembled on the robot is presented. The method is based on the least squares solution of an over-determined linear system obtained with the robot inverse dynamic identification model in which are included the sensor gains. This model is calculated with available sensor measurement and joint position sampled data while the robot is tracking some reference trajectories without load on the robot and some trajectories with a known payload fixed on the robot. The method is experimentally validated on the Kuka LWR4+ but can be applied to any similar kind of robot equipped with joint torque sensors.

## I. INTRODUCTION

Safe interactions between the robot and its environment are required in many new industrial applications such as co-working involving other robots and humans. In this context, the manufacturer Kuka and the German Aerospace Center (DLR) have developed recently a new robot able to evolve in human environment, the Kuka Light-Weight Robot (LWR) [1] (future industrial version: Kuka IIWA). This robot, thanks to additional torque sensors located after the gearbox of each actuated joint, is able to detect and control the interaction of the robot with its environment. However, for obtaining a correct estimation of the interaction using the torque sensors, they must be calibrated with a good accuracy, and this problem requires time-consuming processes [2-4] that: use complicated calibrated devices that are able to apply precise loads on the sensors; use a sensor model that gives the linear relations between the loads and

the measurement signals; build an over-determined linear system of equations in order to decrease the bias due to the measurement noise and estimate the parameter values using Least Squares (*LS*) techniques, this system of equations can be obtained by doing a large number of experiments (see [4] for example), which is a time-consuming process; finally, must be carried out before assembling the sensors on the robot.

In order to avoid these drawbacks, it is proposed in this paper a simpler technique that: can be carried out once the torque sensors are assembled on the robot; use only an accurately weighed payload mass; build the over-determined linear system of equations using data that have been collected while the robot is tracking some exciting trajectories that have a duration of few seconds, as it will be shown further.

This technique is indeed an adaptation of a method that has been recently developed for calibrating the drive gains of the robot actuated joints [5]. This method: allowed the global identification of all robot dynamic parameters, including joint drive gains, by using an Inverse Dynamic Identification Model (*IDIM*) [6-10] that gives the linear relations between the joint forces/torques and the dynamic parameters; used data collected while the robot was tracking reference trajectories without load fixed on the robot and trajectories with a known payload fixed on the robot.

All dynamic parameters and drive gains were calculated in one step as the Total *LS* (*TLS*) solution of an over-determined system that takes into account the dynamic coupling effect between the robot axes. So, it is shown in this paper that, by calculating a linear *IDIM* of the robot with respect to (w.r.t.) the torque sensor data, by adding the torque sensor gains into the parameters to identify and by using a *TLS* identification method, torque sensor gains can be calibrated with a good accuracy. It should be mentioned that this method is easy to implement, allows a fast recording of the experimental data, and is versatile and suitable for the automatic calibration of the sensor gains of LWR-like robots.

The paper is divided as follows. The next Section presents the computation of the *IDIM* of the robot w.r.t. the torque sensor measurements. Then, Section III introduces the identification procedure that will be used for calibrating the sensor gains. Section IV presents the experimental results obtained on the Kuka LWR. Finally, Section V deals with the conclusions.

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## II. COMPUTATION OF THE INVERSE DYNAMIC IDENTIFICATION MODEL

### A. Inverse Dynamic Identification Model (IDIM)

Using the Modified Denavit-Hartenberg (MDH) description of moving multibody systems [9], the dynamic model of any serial manipulator composed of  $n$  links can be linearly written in term of a  $(n_{st} \times 1)$  vector of standard parameters  $\chi_{st}$  [8][9]:

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

where  $\tau_{idm}$  is the joint torque vector at the output of the drive chain,  $q$ ,  $\dot{q}$  and  $\ddot{q}$  are respectively the  $(n \times 1)$  vectors of generalized joint positions, velocities and accelerations,  $IDM_{st}$  is the  $(n \times n_{st})$  jacobian matrix of  $\tau_{idm}$  (1), w.r.t. the vector  $\chi_{st}$  of the standard parameters given by  $\chi_{st} = [\chi_{st}^1 \chi_{st}^2 \dots \chi_{st}^n]^T$ .

For a rigid robot, the link  $j$  and joint  $j$  can be parameterized by 14 standard parameters regrouped into the vector  $\chi_{st}^j$  [9] where  $XX_j, XY_j, XZ_j, YY_j, YZ_j, ZZ_j$  are the six components of the inertia matrix of link  $j$  w.r.t. frame  $j$  at its origin;  $MX_j, MY_j, MZ_j$  are the 3 components of the first moment of link  $j$ ,  $M_j$  is its mass,  $Ia_j$  is a total inertia moment for rotor of actuator  $j$  and gears of the joint  $j$  drive chain;  $Fv_j, Fs_j$  are the viscous and Coulomb friction coefficients of the part of the drive chain between the torque sensor and the output of the drive chain (the link), respectively, and  $\tau_{off_j}$  is an offset parameter that takes into account the offset of the torque sensor of the joint  $j$  and the asymmetry in Coulomb friction coefficient [11].

It should be mentioned that, in the dynamic model that computes the values of the torques on the sensors of the Kuka LWR, the parameters  $Ia_j$  are eliminated as they are related to motor inertias only. There is no potential drift phenomenon on the measurements of torque sensors of this robot so it is unnecessary to take into account this phenomenon in the MDI.

The identifiable parameters are the base parameters, which are the minimal number of dynamic parameters from which the dynamic model can be calculated. They are obtained from the standard parameters by eliminating those which have no effect in (1) and by regrouping some of the other by means of linear relations [12], using simple closed-form rules [9], [13], or by numerical method based on the QR decomposition [14].

The minimal dynamic model can be written using the  $n_b$  base dynamic parameters  $\chi$  as follows:

$$\tau_{idm} = IDM(q, \dot{q}, \ddot{q})\chi \quad (2)$$

where  $IDM$  is a subset of independent columns of  $IDM_{st}$  which defines the identifiable parameters.

Because of perturbations due to noise measurement and modeling errors, the actual force/torque  $\tau$  differs from the model  $\tau_{idm}$  by an error,  $e$ , such that:

$$\tau = \tau_{idm} + e = IDM(q, \dot{q}, \ddot{q})\chi + e \quad (3)$$

where  $\tau$  is the vector of the values of the torques given by the sensors, which is calculated using a linear relation [2]:

$$\tau = v_\tau g_\tau = \text{diag}\left([\nu_\tau^1 \dots \nu_\tau^n]\right) [g_\tau^1 \dots g_\tau^n]^T \quad (4)$$

$v_\tau$  is the  $(n \times n)$  matrix of the actual torque sensor measurement signal ( $\nu_\tau^j$  corresponds to actuator  $j$ ) and  $g_\tau$  is the  $(n \times 1)$  vector of the torque sensor gains ( $g_\tau^j$  corresponds to torque sensor  $j$ ) that is given by *a priori* manufacturer's data or measured with special time-consuming tests when the robot is disassembled [2][3][4].

Equation (3) represents the Inverse Dynamic Identification Model (IDIM).

### B. IDIM with a payload

The payload is considered as a link  $n+1$  fixed to the link  $n$  of the robot [15]. Only  $n_{kl}$  among its ten inertial parameters are considered to be known (i.e. there is  $n_{ul} = 10 - n_{kl}$  unknown parameters). The model (3) becomes:

$$\begin{aligned} \tau &= [IDM \quad IDM_{ul} \quad IDM_{kl}] [\chi^T \quad \chi_{ul}^T \quad \chi_{kl}^T]^T + e \\ &= IDM_{tot} \chi_{tot} + e \end{aligned} \quad (5)$$

where  $\chi_{al}$  ( $a = u$  or  $k$ ) is a  $(n_{al} \times 1)$  vector containing the unknown ( $\chi_{ul}$ ) or known ( $\chi_{kl}$ ) inertial parameters of the payload;  $IDM_{al}$  is the  $(n \times n_{al})$  jacobian matrix of  $\tau_{idm}$ , w.r.t. the vector  $\chi_{al}$ .

## III. GLOBAL IDENTIFICATION OF THE ROBOT DYNAMIC PARAMETERS AND THE TORQUE SENSOR GAINS

### A. Computation of the Over-Determined System of Equations

The off-line identification of the robot base dynamic parameters  $\chi$  can be achieved given measured or estimated off-line data for  $\tau$  and  $(q, \dot{q}, \ddot{q})$ , collected while the robot is tracking some exciting trajectories. The model (3) is sampled, low-pass filtered and decimated 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  $(\hat{q}, \hat{\dot{q}}, \hat{\ddot{q}})$  is an estimation of  $(q, \dot{q}, \ddot{q})$ , obtained by sampling, band-pass filtering the measure of  $q$  [8],  $\rho$  is the  $(r \times 1)$  vector of errors,  $Y(\tau)$  is the  $(r \times 1)$  vector of the sampled sensor torques, and  $W(\hat{q}, \hat{\dot{q}}, \hat{\ddot{q}})$  is the  $(r \times n_b)$  observation matrix. In [16], practical rules for tuning these filters are given.

Using the base parameters and tracking exciting reference trajectories, a well-conditioned matrix  $W$  can be obtained [17]. In this work, the motion generator of the industrial controller which is a Point-To-Point trapezoidal acceleration generator is used. Some trajectories are tested covering the whole robot workspace until a well-conditioned matrix  $W$  is obtained [17][18], which is an easy and fast procedure that gives good identification results.

### B. Identification with a payload

In order to identify both the robot and the payload dynamic parameters, it is necessary that the robot carries out two types of trajectories: (a) trajectories without the payload and (b) trajectories with the payload fixed to the end-effector [15]. The sampling and filtering of the *IDIM* (5) is then written as:

$$Y = \begin{bmatrix} Y_a \\ Y_b \end{bmatrix} = \begin{bmatrix} W_a & 0 & 0 \\ W_b & W_{ul} & W_{kl} \end{bmatrix} \begin{bmatrix} \mathcal{X}^T & \mathcal{X}_{ul}^T & \mathcal{X}_{kl}^T \end{bmatrix}^T + \rho \quad (7)$$

where  $Y_a$  ( $Y_b$ , resp.) is the vector of sampled sensor torques in the unloaded (loaded, resp.) case,  $W_a$  ( $W_b$ , resp.) is the observation matrix of the robot in the unloaded (loaded, resp.) case and  $W_{ul}$  ( $W_{kl}$ , resp.) is the observation matrix of the robot corresponding to the unknown (known, resp.) payload inertial parameters.

### C. Total Least Square Identification of the Robot Dynamic Parameters and the Torque Sensor Gains (*IDIM-TLS*)

To identify the torque sensor gains, it is necessary to introduce them into the robot base parameters and to use a new method developed recently for identify the robot drive gains [5], which is based on a Total Least Squares Identification (*IDIM-TLS*) procedure (see [19-23] for a global overview of the *TLS* techniques). This procedure is detailed below.

Taking into account that parameters  $\mathcal{X}_{kl}$  are known, (7) can be written as:

$$Y = \begin{bmatrix} V_{\tau a} \\ V_{\tau b} \end{bmatrix} \mathcal{G}_{\tau} = \begin{bmatrix} W_a & 0 & 0 \\ W_b & W_{ul} & W_{kl} \mathcal{X}_{kl} \end{bmatrix} \begin{bmatrix} \mathcal{X} \\ \mathcal{X}_{ul} \\ 1 \end{bmatrix} + \rho \quad (8)$$

where  $V_{\tau a}$  ( $V_{\tau b}$ , resp.) is the block-diagonal matrix of  $v_{\tau}$  samples in the unloaded (loaded, resp.) case,

$$V_{\tau a,b} = \begin{bmatrix} V_{\tau}^1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & V_{\tau}^n \end{bmatrix}, \quad V_{\tau}^j = \begin{bmatrix} v_{\tau,1}^j \\ \vdots \\ v_{\tau,r/n}^j \end{bmatrix}, \quad (9)$$

$v_{\tau,k}^j$  is the  $k$ -th sample of measurement data for sensor  $j$ , and  $V_{\tau}^j$  regroups all the measurement data samples for sensor  $j$ .

To fit the *TLS* problem, (8) can be rewritten as:

$$W_{tot} \mathcal{X}_{tot} = \rho, \quad \text{where} \quad (10)$$

$$W_{tot} = \begin{bmatrix} V_{\tau a} & -W_a & 0 & 0 \\ V_{\tau b} & -W_b & -W_{ul} & -W_{kl} \mathcal{X}_{kl} \end{bmatrix} \text{ is a } (r \times c) \text{ matrix}$$

(with  $c = n + n_b + n_{ul} + 1$ ), and  $\mathcal{X}_{tot}^T = [\mathcal{G}_{\tau}^T \quad \mathcal{X}^T \quad \mathcal{X}_{ul}^T \quad 1]$  is a  $c \times 1$  vector.

Without perturbation,  $\rho = 0$  and  $W_{tot}$  must be rank deficient to get the non-null solutions  $\hat{\mathcal{X}}_{tot} = \lambda \hat{\mathcal{X}}_{tot}^n \neq 0$  (where  $\hat{\mathcal{X}}_{tot}^n$  is a vector of unit norm, i.e.  $\|\hat{\mathcal{X}}_{tot}^n\| = 1$ ) depending on a scale coefficient  $\lambda$ . However because of the measurement perturbations,  $W_{tot}$  is a full rank matrix. Therefore, the system (10) is changed to the compatible system closest to (10) w.r.t. the Frobenius norm:

$$\hat{W}_{tot} \hat{\mathcal{X}}_{tot} = 0, \quad \hat{\mathcal{X}}_{tot} = [\hat{\mathcal{G}}_{\tau}^T \quad \hat{\mathcal{X}}^T \quad \hat{\mathcal{X}}_{ul}^T \quad 1]^T \quad (11)$$

where  $\hat{W}_{tot}$  is the  $(r \times c)$  rank deficient matrix, closest to  $W_{tot}$  w.r.t. the Frobenius norm, i.e.  $\hat{W}_{tot}$  minimizes the Frobenius norm  $\|W_{tot} - \hat{W}_{tot}\|_F$  and

$\hat{\mathcal{X}}_{tot} = [\hat{\mathcal{G}}_{\tau}^T \quad \hat{\mathcal{X}}^T \quad \hat{\mathcal{X}}_{ul}^T \quad 1]^T$  is the solution of the compatible system (11) closest to (10).

$\hat{W}_{tot}$  can be computed thanks to the ‘‘economy size’’ Singular Value Decomposition (*SVD*) of  $W_{tot}$  [24]:

$$W_{tot} = U S V^T, \quad (12)$$

where  $U$  and  $V$  are  $(r \times c)$  and  $(c \times c)$  orthonormal matrices, respectively, and  $S = \text{diag}(s_i)$  is a  $(c \times c)$  diagonal matrix with singular values  $s_i$  of  $W_{tot}$  sorted in decreasing order.  $\hat{W}_{tot}$  is given by:

$$\hat{W}_{tot} = W_{tot} - s_c U_c V_c^T, \quad (13)$$

where  $s_c$  is the smallest singular value of  $W_{tot}$  and  $U_c$  ( $V_c$ , resp.) the last columns of  $U$  ( $V$ , resp.) corresponding to  $s_c$ . Then, the normalized optimal solution  $\hat{\mathcal{X}}_{tot}^n$  is given by the last column  $V_c$  of  $V$ ,  $\hat{\mathcal{X}}_{tot}^n = V_c$ .

There is infinity of vectors  $\hat{\mathcal{X}}_{tot} = \lambda \hat{\mathcal{X}}_{tot}^n$  which are solutions of (11) depending on a scale factor  $\lambda$ . The unique solution  $\hat{\mathcal{X}}_{tot}^* = \hat{\lambda} \hat{\mathcal{X}}_{tot}^n$  for the robot can be found by taking into account that the last value  $\hat{\mathcal{X}}_{tot,c}^*$  of  $\hat{\mathcal{X}}_{tot}^*$  must be equal to 1 according to (11), i.e.  $\hat{\lambda} = 1 / \hat{\mathcal{X}}_{tot,c}^n$ , with  $\hat{\mathcal{X}}_{tot,c}^n$  the last value of  $\hat{\mathcal{X}}_{tot}^n$ .

### D. Statistical Analysis

Standard deviations  $\sigma_{\hat{x}_i}$  on the dynamic and sensor gains parameters, are estimated assuming that all errors in data matrix  $W_{tot}$  are independently and identically distributed with zero mean and common covariance matrix  $C_{WW}$  such that

$$C_{WW} = \hat{\sigma}_W^2 I_{r_W}, \quad (14)$$

where  $I_{r_W}$  is the identity matrix of dimension  $(r \times c) \times (r \times c)$

An unbiased estimation of the standard deviation  $\hat{\sigma}_W$  is [20]:

$$\hat{\sigma}_W = s_c / \sqrt{r-c} \quad (15)$$

The covariance matrix of the estimation error is approximated by [20]:

$$C_{\hat{\chi}\hat{\chi}} \approx \hat{\sigma}_W^2 \left( I + \|\hat{\chi}_{1:c-1}\|_2^2 \right) \left( \hat{W}_{tot_{1:c-1}}^T \hat{W}_{tot_{1:c-1}} \right)^{-1} \quad (16)$$

with  $\hat{\chi}_{1:c-1}$  the vector containing the  $c-1$  first coefficients of  $\hat{\chi}_{tot}^*$  and  $\hat{W}_{tot_{1:c-1}}$  a matrix composed of the  $c-1$  first columns of  $\hat{W}_{tot}$ . Finally,  $\sigma_{\hat{\chi}_i}^2 = C_{\hat{\chi}\hat{\chi}}(i, i)$  is the  $i^{\text{th}}$  diagonal coefficient of  $C_{\hat{\chi}\hat{\chi}}$  and the relative standard deviation  $\% \sigma_{\hat{\chi}_i}$  is given by:  $\% \sigma_{\hat{\chi}_i} = 100 \sigma_{\hat{\chi}_i} / |\hat{\chi}_i|$ , for  $|\hat{\chi}_i| \neq 0$ .

In order to improve the estimation of  $\hat{\chi}_{tot}^*$ , the rows of  $W_{tot}$  are weighted taking into account the confidence on the measures. As proposed in *IDIM-WLS* (Section II.B), to improve the *TLS* solution, each row corresponding to joint  $j$  equation is weighted by the inverse of  $\hat{\sigma}_W^j$ , i.e. the standard deviation corresponding to the data of the joint  $j$  equations. Moreover, to take into account that the confidence on data in  $V_{\tau a, b}$  is higher than for data in  $W_{a, b}$  and  $W_{u, kl}$ , the columns of  $V_{\tau a, b}$  could also be weighted. However, our experiments have shown that the results were not really improved; therefore this last weighting procedure was not used in the next section.

#### IV. EXPERIMENTAL VALIDATIONS

##### A. Description of the Kinematics and of the KRC Controller of the Kuka LWR

The Kuka LWR (Fig. 1) has a serial structure with seven rotational joints. Its kinematics is defined using the *MDH* notation [9]. 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 I. The payload is denoted as the link 8. The parameter  $\sigma_j = 0$ , means that joint  $j$  is rotational,  $\alpha_j$  and  $d_j$  parameterize the angle and distance between  $z_{j-1}$  and  $z_j$  along  $x_{j-1}$ , respectively, whereas  $\theta_j$  and  $r_j$  parameterize the angle and distance between  $x_{j-1}$  and  $x_j$  along  $z_j$ , respectively. For link 8,  $\sigma_j = 2$  means that the link 8 is fixed on the link 7. Since all the joints are rotational then  $\theta_j$  is the position variable  $q_j$  of joint  $j$ .

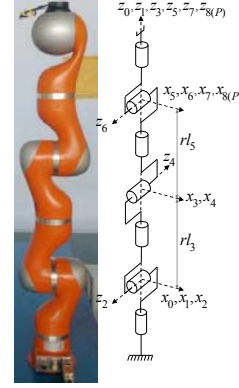


Fig. 1. Link frames of the Kuka LWR.

The KRC controller of the Kuka LWR can provide all necessary data for the identification using an internal special function called “Recorder”.

The joint position  $q_j$  (estimated at the end of the gearbox) are calculated from both the motor position  $q_{mj}$  and the value  $\tau_j$  of the torques given by the sensors using the formula:

$$q_j = q_{mj} / N_j - \tau_j / K_{ap_j}, \quad (17)$$

where  $N_j$  is the joint  $j$  gearbox ratio ( $N_j=160$  for all joints, except for joint 5 for which  $N_5=100$ ), and  $K_{ap_j}$  is an estimated value of the joint  $j$  stiffness (from the manufacturer,  $K_{ap_j} = 10000$  N.m/rad for the first five joints,  $K_{ap_j} = 7500$  N.m/rad for the last two joints).

The torque sensor data are also provided via the use of the “Recorder” function. The sensors being already calibrated by the manufacturer, the information is directly given in N.m. As a result, we won’t be able to identify the absolute value of the sensor gains taken by the manufacturer to calculate  $\tau_j$  (that is *a priori* fixed to  $g_{\tau_j}=1$  in the following of the paper –  $\tau_j = v_{\tau_j} g_{\tau_j}$  with  $g_{\tau_j}=1$ ), but their relative values w.r.t. the nominal (unknown) ones.

TABLE I GEOMETRIC PARAMETERS OF THE KUKA LWR WITH THE PAYLOAD

$j$	$\sigma_j$	$\alpha_j$	$d_j$	$\theta_j$	$r_j$
1	0	0	0	$q_1$	0
2	0	$\pi/2$	0	$q_2$	0
3	0	$-\pi/2$	0	$q_3$	$r_l = 0.4000$ m
4	0	$-\pi/2$	0	$q_4$	0
5	0	$\pi/2$	0	$q_5$	$r_l = 0.3900$ m
6	0	$\pi/2$	0	$q_6$	0
7	0	$-\pi/2$	0	$q_7$	0
8(P)	0	0	0	0	0



Fig. 2. The payload of 4.6136kg for the Kuka LWR.

## B. Identification Results

To validate the proposed method, a calibrated payload is used (Fig. 1). Its mass has been measured with an accurate weighing machine ( $M_8 = 4.6136\text{kg} \pm 0.1 \text{ gr}$ ).

The robot sensors gains and dynamic parameters are identified using the proposed method that requires the definition of two types of exciting trajectories: (not shown here for reason of paper compactness): trajectories without payload and trajectories with the payload.

It must be mentioned that the exciting trajectories consist of 13 via-points (given in the joint space) that make the robot moving in most of its workspace areas. The motion profiles are trapezoidal acceleration profiles and the total motion has a duration of 24 seconds by trajectory (only two trajectories are used in the following of the paper).

TABLE II IDENTIFIED DYNAMIC PARAMETERS

Param.	Value	$\% \sigma_{\hat{\lambda}_n}$	Param.	Value	$\% \sigma_{\hat{\lambda}_n}$
$g_{c1}$	<b>1.02e+00</b>	0.42	$MY_{4R}$	-1.38e+00	0.21
$g_{c2}$	<b>1.01e+00</b>	0.16	$FS_4$	4.33e-01	2.42
$g_{c3}$	<b>1.02e+00</b>	0.16	$MY_{5R}$	3.64e-02	2.07
$g_{c4}$	<b>1.02e+00</b>	0.18	$\tau_{off5R}$	4.29e-01	1.77
$g_{c5}$	<b>1.02e+00</b>	0.48	$FV_5$	-1.19e-01	5.58
$g_{c6}$	<b>1.05e+00</b>	0.53	$FS_5$	1.11e+00	1.09
$g_{c7}$	<b>9.90e-01</b>	0.52	$MY_{6R}$	3.60e-02	2.46
$FS_1$	3.91e-01	3.67	$\tau_{off6R}$	-5.70e-01	1.18
$XX_{2R}$	1.28e+00	1.12	$FS_6$	1.26e-01	4.88
$ZZ_{2R}$	1.30e+00	0.85	$\tau_{off7R}$	2.93e-01	1.07
$MY_{2R}$	3.51e+00	0.23	$FS_7$	1.08e-01	2.66
$\tau_{off2R}$	6.00e-01	3.21	$XY_8$	2.03e-02	3.32
$FS_2$	5.36e-01	3.80	$ZZ_8$	3.79e-02	3.06
$FS_3$	4.93e-01	1.33	$MX_8$	2.65e-01	0.49
$XX_{4R}$	4.61e-01	0.62	$MY_8$	-2.72e-01	0.48
$ZZ_{4R}$	4.55e-01	0.61	$M_8$	4.6136	–

Before presenting the identification result, it is to be noticed that during identification process, some small parameters remain poorly identifiable because they have no significant contribution in the joint torques. These parameters can be cancelled in order to keep a set of essential parameters of a simplified dynamic model with a good accuracy [15]. The essential parameters are calculated

using an iterative procedure starting from the base parameters estimation. At each step the base parameter which has the largest relative standard deviation is cancelled. A new  $LS$  parameter estimation of the simplified model is carried out with new relative error standard deviation  $\% \sigma_{\hat{\lambda}_n}$ . The procedure ends when  $\max(\% \sigma_{\hat{\lambda}_n}) / \min(\% \sigma_{\hat{\lambda}_n}) < r_\sigma$ , where  $r_\sigma$  is a ratio ideally chosen between 10 and 30 depending on the level of perturbation in  $Y$  and  $W$ . Here, for all identification procedures,  $r_\sigma$  is fixed to 30.

The obtained results are shown in Table II. The parameters with the subscript  $R$  stand for the regrouped parameters [9]. The results show that the estimation of the sensor gains is very good (the relative standard deviation is inferior to 0.6%) and that the relative error w.r.t. their nominal value is lower than 5%.

## C. Cross Validations

In order to cross-validate the results, another trajectory, different from the one for the identification (not shown here for reason of paper compactness), is performed with the robot on which is fixed the payload. The positions and torque sensor measures are recorded during the robot displacements. Then, the observation matrix is computed for each trajectory. The sensor torques calculated with the relation (4)  $\tau = v_\tau \hat{g}_\tau$  (where  $v_\tau$  is the measured sensor data and  $\hat{g}_\tau$  the vector of the estimated sensor gains) are compared with torques computed using the  $IDIM$  (2)  $\tau = IDM \hat{\chi}$  ( $\hat{\chi}$  are the identified dynamic parameters) in two cases: first, sensor gains and robot/payload dynamic parameters identified with the  $IDIM-TLS$  method introduced in this paper (Table II). Second, sensor gains given by the manufacturer ( $\hat{g}_{\tau j} = 1$ , for  $j=1, \dots, 7$ ) and robot/payload dynamic parameters identified with a usual  $IDIM$  Weighted- $LS$  ( $WLS$ ) method [15].

For each experiment, the relative error norms  $\|\rho^j\| / \|Y^j\|$  ( $Y^j$  being the sampled value of the sensor torque and  $\rho^j$  the error on the torque reconstruction) computed on each joint  $j$  equation are given in Table III. It is

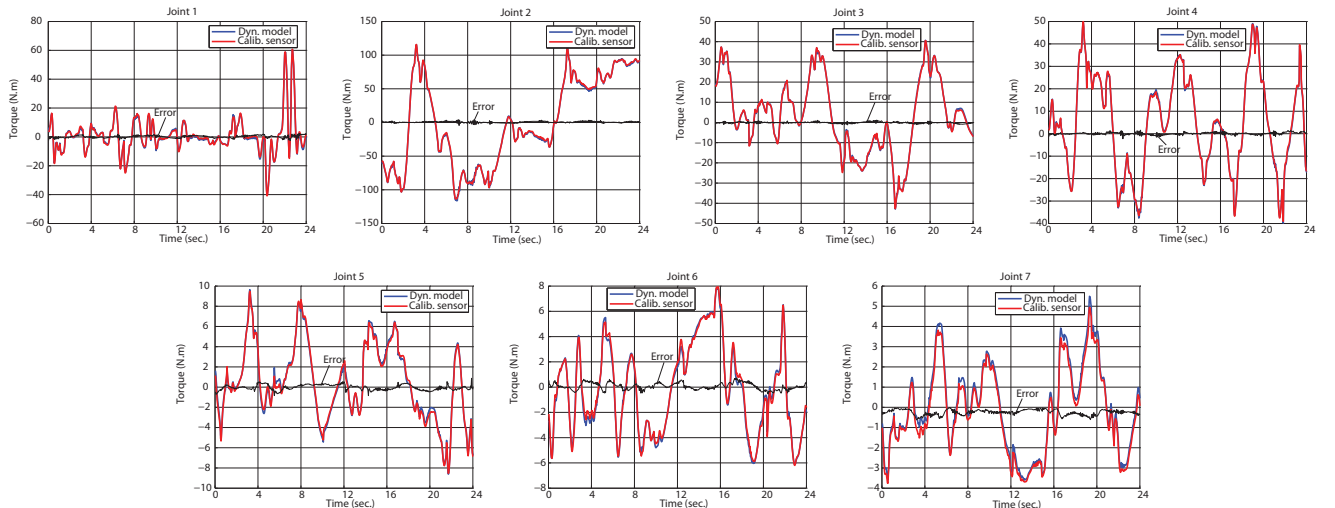


Fig. 3. Measured and reconstructed torques of the KUKA LWR with the parameters identified in Table II.

shown that, with the calibrated gains, the torque estimation is slightly better for most of the joints.

The measured and reconstructed torques of the Kuka LWR with the parameters identified in Table II (Case 1) are shown in Fig. 3 (they are not presented for the parameters of the Case 2 are the results are very similar). It can be observed that the model fits well with the sensor data.

In order to definitely validate our method, a second payload of  $1.7073\text{kg}\pm 0.1\text{gr}$  is attached on the end-effector and the same experiences are performed. Then, using the data collected on each trajectory, the payload is estimated using a usual *IDIM-WLS* [15], in which the actuator torques are calculated with the relation (4)  $\tau = v_r \hat{g}_r$ . The same different values of  $\hat{g}_r$  are considered. The results in terms of payload mass estimation are given in Table IV. They show that the mass is better identified with the new torque sensor gains.

All these result show the effectiveness of this approach: for calibrating the sensor gains, it is only necessary to weigh the payload mass and to carry out standard trajectories of industrial robot. And the calibration of the sensor gains improves the torques and estimation of the payload fixed on the end-effector.

TABLE III QUALITY OF TORQUE RECONSTRUCTION.

Rel. Err. Norm joint 1 joint 2 joint 3 joint 4 joint 5 joint 6 joint 7							
$\ \hat{\rho}'\ /\ \rho'\ $							
Case 1	0.0740	0.0178	0.0226	0.0238	0.0693	0.0775	0.1279
Case 2	0.0741	0.0182	0.0222	0.0241	0.0688	0.0866	0.1278

TABLE IV QUALITY OF PAYLOAD RECONSTRUCTION.

	$\hat{M}_g$	$\% \sigma_{z_g}$
Case 1	1.65	0.28
Case 2	1.59	0.28

## V. CONCLUSION

This paper has presented a new method for the calibration of the torque sensors of the LWR robot. This method is easy to implement, does not need any special test or measurement on the sensors and does not require to disassemble the robot. It is based on a *IDIM-TLS* technique using torque sensor measurements and joint position sampled data while the robot is tracking some reference trajectories without load fixed on the robot and some trajectories with a known payload fixed on the robot end-effector. The payload mass must be only accurately weighed. The method has been successfully experimentally validated on a Kuka LWR. This approach is very simple to perform and the experimental results have shown its effectiveness: for identify the torque sensor gains, it is only necessary to accurately weigh the payload mass and to carry standard trajectories.

## REFERENCES

[1] R. Bischoff, J. Kurth, G. Schreiber, R. Koeppel, A. Albu-Schäffer, A. Beyer, O. Eiberger, S. Haddadin, A. Stemmer, G. Grunwald, and G. Hirzinger, "The KUKA-DLR Lightweight Robot arm - a new reference platform for robotics research and manufacturing," International Symposium on Robotics (ISR), 2010, pp. 1–8.

[2] D. Braun and H. Wörn, "Techniques for Robotic Force Sensor Calibration," International workshop on Computer Ccience and Information Technologies, 2011, pp. 211–223.

[3] R. Voyles, J. Morrow, and P. Khosla, "Shape from Motion Approach to Rapid and Precise Force/Torque Sensor Calibration," *ASME International Mechanical Engineering Congress and Exposition*, 1995.

[4] "Installation and Operations Manual for F/T Series Force/Torque Sensing Systems." Lord Corporation, 1986.

[5] M. Gautier and S. Briot, "Global identification of drive gains parameters of robots using a known payload," IEEE International Conference on Robotics and Automation, 2012, pp. 2812–2817.

[6] G. Antonelli, F. Caccavale, and P. Chiacchio, "A systematic procedure for the identification of dynamic parameters of robot manipulators," *Robotica*, vol. 17, no. 4, pp. 427–435, 1999.

[7] K. Kozłowski, *Modelling and Identification in Robotics*. Springer London, 1998.

[8] J. Hollerbach, W. Khalil, and M. Gautier, "Model Identification," in *Springer Handbook of Robotics*, Springer, 2008.

[9] W. Khalil and E. Dombre, *Modeling, Identification and Control of Robots*, 3rd edition. New York: Taylor and Francis Group, 2002.

[10] P. K. Khosla and T. Kanade, "Parameter identification of robot dynamics," IEEE Conference on Decision and Control, 1985, pp. 1754–1760.

[11] P. Hamon, M. Gautier, and P. Garrec, "New dry friction model with load- and velocity-dependence and dynamic identification of multi-DOF robots," IEEE International Conference on Robotics and Automation, 2011, pp. 1077–1084.

[12] H. Mayeda, K. Yoshida, and K. Osuka, "Base parameters of manipulator dynamic models," *IEEE Transactions on Robotics and Automation*, pp. 312–321, 1990.

[13] M. Gautier and W. Khalil, "Direct calculation of minimum set of inertial parameters of serial robots," *IEEE Transactions on Robotics and Automation*, pp. 368–373, 1990.

[14] M. Gautier, "Numerical calculation of the base inertial parameters of robots," IEEE International Conference on Robotics and Automation, 1990, vol. 2, pp. 1020–1025.

[15] W. Khalil, M. Gautier, and P. Lemoine, "Identification of the payload inertial parameters of industrial manipulators," IEEE International Conference on Robotics and Automation, 2007, pp. 4943–4948.

[16] M. Gautier, "Dynamic identification of robots with power model," IEEE International Conference on Robotics and Automation, 1997, vol. 3, pp. 1922–1927.

[17] J. Swevers, C. Gansema, D. B. Tukel, J. De Schutter, and H. Van Brussel, "Optimal Robot Excitation and Identification," *IEEE Transactions on Robotics and Automation*, vol. 13, no. 5, pp. 730–740, 1997.

[18] C. Presse and M. Gautier, "New criteria of exciting trajectories for robot identification," IEEE International Conference on Robotics and Automation, 1993, pp. 907–912.

[19] C. R. Rao and H. Toutenburg, *Linear Models: Least Squares and Alternatives*. Springer Series in Statistics, 1999.

[20] S. Van Huffel and J. Vandewalle, *The Total Least Squares Problem: Computational Aspects and Analysis*. Philadelphia, Pennsylvania:: SIAM, 1991.

[21] I. Markovsky and S. Van Huffel, "Overview of total least-squares methods," *Signal Processing*, vol. 87, no. 10, 2007.

[22] I. Markovsky, D. Sima, and S. Van Huffel, "Total Least Squares Methods," *Wiley Interdisciplinary Reviews: Computational Statistics*, vol. 2, pp. 212–217, 2002.

[23] S. Van Huffel, "The Generalized Total Least Squares Problem: Formulation, Algorithm and Properties," *Numerical Linear Algebra, Digital Signal Processing and Parallel Algorithms*, vol. 2, pp. 651–660, 1991.

[24] G. H. Golub and C. F. Van Loan, *Matrix Computations*. J. Hopkins 2nd Ed. Baltimore, 1983.