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Joint Stiffness Identification from only Motor Force/Torque Data

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Abstract—**This paper deals with joint stiffness identification with only actual motor force/torque data instead of motor and load positions. The parameters are estimated by using the DIDIM method which needs only input data. This method was previously validated on a 6 DOF rigid robot and is now extended to flexible systems. The criterion to be minimized is the quadratic error between the measured actual motor force/torque and the simulated one. The optimal parameters are calculated with the Nelder – Mead simplex algorithm. An experimental setup exhibits the experimental identification results and shows the effectiveness of our approach.**

I. INTRODUCTION

ACCURATE dynamic robots models are needed to control and simulate their motions. Identification of rigid robots has been widely investigated in the last decades. The usual identification process is based on the inverse dynamic model and the ordinary or weighted least squares estimation. This method, called IDIM, has been performed on several prototypes and industrial robots with accurate results [1][2][3][4][5].

Identification of flexibilities is more complex than the identification of rigid body dynamics. Indeed, only a subset of state variables is measured [6] and one can not use directly linear regressions [5]. This can be solved by adding sensors [7] and/or external excitations [8]. In [9], the authors use the System Identification Toolbox for Matlab [10][11] to identify both joint and structural flexibilities of one axis of an industrial robot. The approach is interesting because inertia and stiffness parameters seem well identified. But, they do not discuss about the repartition of Coulomb friction and data filtering. In [12] and [13], the authors have developed some minimal identification models depending on the measurements availability. Furthermore, they have designed a data filtering process relevant for joint stiffness identification. The experimental results are convincing.

Though these techniques provide good results, they need at least two measurements: actual torque/force data and motor position.

Recently, a new identification process needing only actual force/torque data was first validated on a 2 DOF rigid prototype [19] and then validated on a 6 DOF rigid robot [18]. Experimental results show the effectiveness of this method called DIDIM. Then it is extended to joint stiffness identification.

This paper is divided into five sections. Section II describes the experimental setup and its modeling. Section III presents the classical identification method called IDIM while section IV presents the new identification method called DIDIM. Section V is devoted to the experimental identification based on IDIM method and DIDIM method extended to flexible systems.

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II. MODELING OF A FLEXIBLE JOINT ROBOT

A. *Experimental setup*

The EMPS is a high-precision linear Electro-Mechanical Positioning System (see Fig. 1). It is a standard configuration of a drive system for prismatic joint of robots or machine tools.

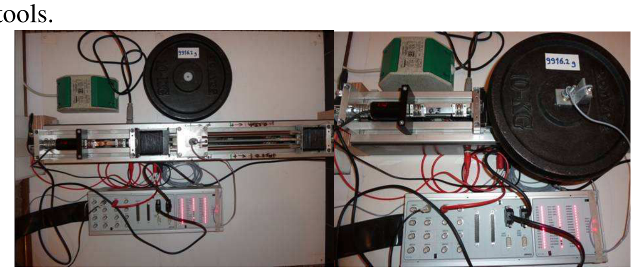

Fig. 1. EMPS prototype to be identified

Its main components are:

- A Maxon DC motor equipped with an incremental encoder. This DC motor is position controlled with a PD controller.

- A Star high-precision low-friction ball screw drive positioning unit. An incremental encoder at its extremity supplies information about the angular position of the screw.

- A load in translation.

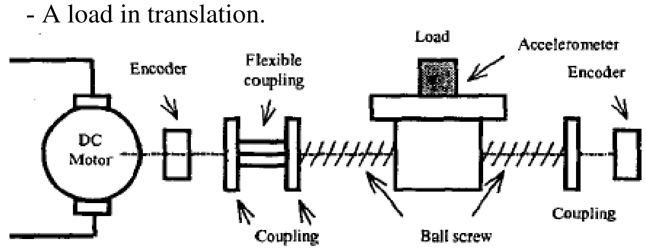

Fig. 2. EMPS Components

These components are presented Fig. 2. All variables and parameters are given in ISO units on the load side.

B. Rigid inverse dynamic model

In this case, the system is modeled with one inertia and frictions. The inverse dynamic model (IDM) expressing the motor torque according to the state and its derivatives is:

$$\tau_1 = ZZ_{1R}\ddot{q}_1 + F_{v1R}\dot{q}_1 + F_{c1R}sign(\dot{q}_1) \quad (1)$$

Where, q_1, $\dot{q}_1$, $\ddot{q}_1$ are respectively the motor position, velocity and acceleration; τ_1 is the motor torque; ZZ_{1R} is the total inertia; F_{v1R} and F_{c1R} are the total viscous and Coulomb friction parameters.

C. The flexible dynamic model

In this case, the mechanical system can be modeled with two inertias, frictions, a spring and a damping, Fig. 3.

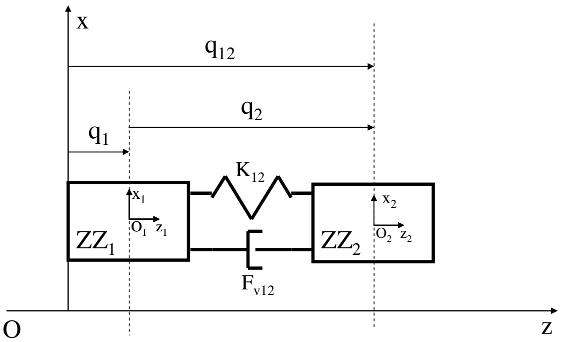

Fig. 3. EMPS modeling and DHM frames

With Newton – Euler equations [5], we obtain the following inverse dynamic model:

$$\begin{aligned} \tau_1 &= ZZ_1\ddot{q}_1 + F_{v1}\dot{q}_1 + F_{c1}sign(\dot{q}_1) - K_{12}q_2 - F_{12}\dot{q}_2 \\ 0 &= ZZ_2\ddot{q}_{12} + F_{v2}\dot{q}_{12} + F_{c2}sign(\dot{q}_{12}) + K_{12}q_2 + F_{12}\dot{q}_2 \end{aligned} \quad (2)$$

Where: q_1, $\dot{q}_1$, $\ddot{q}_1$ are respectively the motor position, velocity and acceleration; τ_1 is the motor torque; q_{12}, $\dot{q}_{12}$, $\ddot{q}_{12}$ are respectively the load position, velocity and acceleration; q_2, $\dot{q}_2$, $\ddot{q}_2$ are respectively the elastic DOF position, velocity and acceleration with, $q_{12} = q_1 + q_2$, $\dot{q}_{12} = \dot{q}_1 + \dot{q}_2$ and $\ddot{q}_{12} = \ddot{q}_1 + \ddot{q}_2$; ZZ_1 is the motor inertia, F_{v1} and F_{c1} are respectively the viscous and Coulomb motor friction parameters; ZZ_2 is the load inertia, F_{v2} and F_{c2} are respectively the viscous and Coulomb load friction parameters; K_{12} is the stiffness and F_{12} the damping.

The inverse dynamic model (2) can be written as follows:

$$\tau_{idm} = M(q)\ddot{q} + N(q,\dot{q}) + Kq + B\dot{q} \quad (3)$$

With: $q = \begin{pmatrix} q_1 \\ q_{12} \end{pmatrix}$ $\dot{q} = \begin{pmatrix} \dot{q}_1 \\ \dot{q}_{12} \end{pmatrix}$ $\ddot{q} = \begin{pmatrix} \ddot{q}_1 \\ \ddot{q}_{12} \end{pmatrix}$ $\tau_{idm} = \begin{pmatrix} \tau_1 \\ 0 \end{pmatrix}$ $M(q) = \begin{pmatrix} ZZ_1 & 0 \\ 0 & ZZ_2 \end{pmatrix}$

$N(q,\dot{q}) = \begin{pmatrix} F_{v1}\dot{q}_1 + F_{c1}sign(\dot{q}_1) \\ F_{v2}\dot{q}_{12} + F_{c2}sign(\dot{q}_{12}) \end{pmatrix}$ $K = \begin{pmatrix} K_{12} & -K_{12} \\ -K_{12} & K_{12} \end{pmatrix}$ $B = \begin{pmatrix} F_{v12} & -F_{v12} \\ -F_{v12} & F_{v12} \end{pmatrix}$

The direct dynamic model (DDM) is then described by:

$$M(q)\ddot{q} = \tau_{idm} - N(q,\dot{q}) - Kq - B\dot{q} \quad (4)$$

The inverse dynamic model (2) can be written in a linear relation to the dynamic parameters as follows:

$$\tau_{idm} = IDM_{ST}\chi_{ST} \quad (5)$$

With: $\tau_{idm} = (\tau_1 \quad 0)^T$

$\chi_{ST} = (ZZ_1 \quad F_{v1} \quad F_{c1} \quad K \quad B \quad ZZ_2 \quad F_{v2} \quad F_{c2})^T$

$D_{STD} = \begin{pmatrix} \ddot{q}_1 & \dot{q}_1 & sign(\dot{q}_1) & -q_2 & -\dot{q}_2 & 0 & 0 & 0 \\ 0 & 0 & 0 & q_2 & \dot{q}_2 & \ddot{q}_{12} & \dot{q}_{12} & sign(\dot{q}_{12}) \end{pmatrix}$

There are 8 parameters to be identified called standard parameters. Because all the standard parameters are identifiable [14][15], the minimal identification model is in fact the standard model given by (5). So, we get:

$IDM = IDM_{ST}$, $\chi = \chi_{ST}$ and $\tau_{idm} = (\tau_1 \quad 0)^T$ (6)

III. IDIM: INVERSE DYNAMIC IDENTIFICATION METHOD

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

$$\tau = \tau_{idm} + e = IDM(q,\dot{q},\ddot{q})\chi + e \quad (7)$$

The identification method developed for the manipulator robots is applied for flexible systems. The vector χ is estimated with ordinary least squares (OLS) technique thanks to an over determined system built from the sampling of (7):

$$Y = W\chi + \rho \quad (8)$$

Where: Y is the (rx1) measurement vector, W the (rxb) regressor, χ is the (bx1) vector of parameters to be identified and ρ is the (rx1) residual vector. We have $r = n * n_e$, where n_e is the number of collected samples.

The unicity of the OLS solution is ensured if W is a full rank matrix i.e. if $rank(W) = b$. To avoid rank deficiency, only the b base parameters must be considered [14][15] and trajectories must be exciting enough [16][17].

The detailed calculation of the standard deviation $\sigma_{\hat{\chi}_j}$ and the relative standard derivation $100 * \left|\sigma_{\hat{\chi}_j} / \hat{\chi}_j\right|$ for $\hat{\chi}_j \neq 0$ can be found in [3] for instance.

Calculating the OLS solution of (8) from noisy discrete measurements or estimations of derivatives may lead to bias. Indeed W may be correlated to ρ. However, it has been shown that OLS estimation is as consistent as robust estimation methods such as instrumental variable method (see [21] for instance) provided a well tuned bandpass filtering. Then, it is essential to filter data in Y and W before computing the OLS solution.

Velocities and accelerations are estimated by means of a band pass filtering of the positions. This band pass filtering is obtained with the product of a low pass filter in both forward and reverse direction (Butterworth) and from a derivative filter obtained by central difference algorithm, without phase shift. To eliminate high frequency noises and torque ripples, a parallel decimation is performed on Y and the columns of W. This low pass decimate filter resamples each signal at a lower rate. More details about data filtering can be found in [3][12][13].

IV. DIDIM: Direct and Inverse Dynamic Identification Model Technique

A. Theoretical approach for rigid systems

In this section, DIDIM method is briefly recalled. A complete presentation of DIDIM can be found in [18].
DIDIM is a closed loop output error (CLOE) method requiring only torque data. The output $y = \tau$, is the actual joint force/torque τ, and the simulated output $y_s = \tau_{idm}$, is the simulated joint force/torque.

The signal $q_{ddm}(\chi, t)$ is the result of the integration of the linear implicit differential equation. The optimal solution $\hat{\chi}$ minimizes the following quadratic criterion:

$$J(\chi) = \|Y - Y_S\|^2 \tag{9}$$

Where $Y(\tau)$ and $Y_S(\tau_{idm})$ are vectors obtained by filtering and downsampling the vectors of samples of the actual force/torque τ, and of the simulated force/torque τ_{idm}, respectively.

This non-linear LS problem is solved by the Gauss-Newton regression. It is based on a Taylor series expansion of y_s, at a current estimate $\hat{\chi}^k$. Because of the same closed loop control for the actual and for the simulated robot and the gains tuning of the simulated controller, the simulated position, velocity and acceleration have little dependence on χ. Then the jacobian matrix can be approximated by:

$$\left(\frac{\partial(y_S)}{\partial\chi}\right)_{\hat{\chi}^k} \approx IDM\left(q_{ddm}(\hat{\chi}^k), \dot{q}_{ddm}(\hat{\chi}^k), \ddot{q}_{ddm}(\hat{\chi}^k)\right) \tag{10}$$

Taking the approximation (10) of the jacobian matrix into the Taylor series expansion, it becomes:

$$y = \tau = IDM\left(q_{ddm}(\hat{\chi}^k), \dot{q}_{ddm}(\hat{\chi}^k), \ddot{q}_{ddm}(\hat{\chi}^k)\right)\chi^{k+1} + (o + e) \tag{11}$$

This is the Inverse Dynamic Identification Model, IDIM, (1), where $(q, \dot{q}, \ddot{q})$ are estimated with $(q_{ddm}, \dot{q}_{ddm}, \ddot{q}_{ddm})$, got from the simulated direct dynamic model. The sampling of (11) and after a parallel decimation, we get an over-determined linear system:

$$Y(\tau) = W_\delta\left(q_{ddm}, \dot{q}_{ddm}, \ddot{q}_{ddm}, \hat{\chi}^k\right)\chi + \rho \tag{12}$$

The LS solution of (12) calculates $\hat{\chi}_{k+1}$, at iteration $k+1$. This process is iterated until: $(\|\rho_{k+1}\| - \|\rho_k\|) / \|\rho_k\| \le tol_1$

Where tol_1 is a value ideally chosen to be a small number to get fast convergence with good accuracy.

B. Theoretical approach for flexible systems

The approximation of the jacobian matrix given by (10) is violated for flexible systems because the load states (i.e. q_{12}, $\dot{q}_{12}$) are not controlled. Then, we can not ensure that the simulated position, velocity and acceleration have little dependence on χ.

The optimal solution $\hat{\chi}$ still minimizes the quadratic criterion given by (9). We get always the simulated states from simulating (4); the matrices $M(q_{ddm}, \chi)$ and $N(q_{ddm}, \dot{q}_{ddm}, \chi)$ being defined by (3). But, in this case, the non-linear LS problem is solved by using the Nelder – Mead simplex algorithm as described in [20].

This algorithm is used by "*fminsearch*" MATLAB function and it is suitable for low dimensional problems. Since we have 8 base parameters to identify, this algorithm is adapted to our problem.

C. Initialization of the algorithm

In [18], the authors have proposed an efficient way to initialize DIDIM algorithm. This initialization, called regular initialization, is based on gains tuning of the simulated controller according to $\hat{\chi}^k$.

Unfortunately, this initialization can not be applied to flexible systems (the load states are not controlled). So, we must find another way to initialize the DIDIM algorithm.

Since it is always possible to identify the "rigid" values, we can use them for initializing our algorithm. Then, the simplest way is the following:
- First, identify the "rigid" values with DIDIM method,
- Second, divide them by 2 to get the initial values.

Finally, it comes: $ZZ_1^0 = ZZ_2^0 = ZZ_T / 2$, $F_{v1}^0 = F_{v2}^0 = F_{vT} / 2$ and $F_{c1}^0 = F_{c2}^0 = F_{cT} / 2$ (13)

This initialization is called "pseudo regular initialization" and it is dedicated to joint stiffness identification.

V. Experimental validation

A. Data acquisition

Motor and load positions are measured by means of high precision encoders working in quadrature count mode (accuracy of 100000 counts per revolution). The sample acquisition frequency for joint position and current reference (drive force) is 1 KHz.

We calculate the motor torque using the relation:

$$\tau_1 = G_\tau v_\tau \tag{14}$$

where v_τ is the current reference of the amplifier current loop, and G_τ is the gain of the joint drive chain, which is taken as a constant in the frequency range of the robot because of the large bandwidth (700 Hz) of the current loop.

The first natural frequency, ω_n, is of 30Hz. This was verified with appropriate mechanical experiments such as blocked output test (see [4] for instance).

The system is position controlled with a PD controller and the bandwidth of the closed loop is tuned at 30Hz to identify the dynamic parameters.

Exciting trajectories consist of trapezoidal velocity with pulses. Trapezoidal velocity excites very well inertia and friction parameters while pulses excite flexibility. We have $cond(W)=30$. The parameters are well excited and can be identified [16][17].

B. Identification of the rigid dynamic model

The rigid dynamic model is valid at low frequencies (less than 10Hz). Hence, the cut-off frequency of band pass and decimate filter is fixed at 5Hz. DIDIM is performed (only the actual motor force/torque is needed). Because we identify the rigid model, the algorithm is initialized with the regular initialization and the gains of the simulated controller are updated (see [19] for more details). The algorithm converges in only 2 steps and the "rigid" DIDIM identified values are given in Table 1.

TABLE 1. DIDIM IDENTIFIES VALUES WITH THE RIGID MODEL

Parameter	$\hat{\chi}_j$	$2*\sigma_{\hat{\chi}_j}$	$100*\left\|\sigma_{\hat{\chi}_j}/\hat{\chi}_j\right\|$
ZZ_{1R}	106	0.44	0.21
F_{v1R}	208	3.5	0.84
F_{c1R}	20.0	0.35	0.88

C. Identification of the flexible model with no additional mass on the load

The cut-off frequency of band pass and decimate filter is fixed at 60Hz. We keep one sample over 12.

With the identification model described by (4), the maximum derivatives order is 2. Hence, according to [12], the order of Butterworth filter is fixed at 4. IDIM is performed. Motor, load positions and actual motor force/torque are measured. The results are given in Table 2. In addition, the estimated natural frequency and $\left\|(Y-W\hat{\chi})\right\|/\left\|Y\right\|$, the relative norm of the residue, are given.

Cross tests validations have been performed. They consist in simulating the EMPS with the identified values. The estimated torque follows closely the measured one (see Fig. 4). Furthermore, the relative norm of the error between the measured torque and the simulated one, $\left\|\left(Y-\hat{Y}_S\right)\right\|/\left\|Y\right\|$, is computed and given in Table 3.

Now, DIDIM is performed and only the actual motor force/torque is needed. We get the simulated states by simulating (4); the matrices $M\left(q_{ddm},\chi\right)$ and $N\left(q_{ddm},\dot{q}_{ddm},\chi\right)$ being defined by (3). The motor force/torque is computed with (14). The columns of the observation matrix are decimated. The optimal values are estimated with "*fminsearch*" MATLAB function. The algorithm is initialized with the pseudo regular initialization (13). The algorithm converges in 25 iterations. The results are given in Table 3. In addition, the estimated natural frequency and $\left\|\left(Y-\hat{Y}_S\right)\right\|/\left\|Y\right\|$, the relative norm of the residue, are given.

Direct validation has been performed. The estimated torque follows closely the measured one as illustrated Fig. 5.

Since both motor and load positions are measured, the identification results provided by IDIM are the most accurate and can be thus considered as the referee values. By adding inertia, viscous and Coulomb friction parameters, we retrieve practically the "rigid" values.

DIDIM provides excellent results although only one measurement is used (see Table 3). All parameters are well identified and they are very close to those given in Table 2, excepted for F_{v1} and F_{v2}. These values are permutated. Perhaps it is quite difficult to dissociate properly the viscous friction (motor side and load side) with only torque data. Finally, by adding inertia, viscous and Coulomb friction parameters, we retrieve practically the "rigid" values. The relative errors between IDIM and DIDIM identified values have been computing and summed in Table 7

The relative errors are given by the following simple formula:

$$\%e\left(\chi_j\right)=100\left|\left(\hat{\chi}_j^{IDIM}-\hat{\chi}_j^{DIDIM}\right)/\hat{\chi}_j^{DIDIM}\right| \quad (15)$$

Where $\hat{\chi}_j^{IDIM}$ is the IDIM identified value of the j^th^ parameter and $\hat{\chi}_j^{DIDIM}$ is the DIDIM identified value of the j^th^ parameter.

TABLE 2: OLS IDENTIFIED VALUES WITH THE FIRST MINIMAL IDENTIFICATION MODEL

Parameter	$\hat{\chi}_j$	$2*\sigma_{\hat{\chi}_j}$	$100*\left\|\sigma_{\hat{\chi}_j}/\hat{\chi}_j\right\|$
ZZ_1	70.2	0.20	0.14
F_{v1}	92.0	1.89	1.03
F_{c1}	10.0	0.47	2.35
K_{12}	$8.0\ 10^5$	$3.0\ 10^3$	0.19
F_{v12}	126.0	36.0	14.3
ZZ_2	34.8	0.19	0.27
F_{v2}	110.0	1.69	0.76
F_{c2}	10.4	0.15	0.72
Estimated natural frequency: 29.0Hz			
$\left\|(Y-W\hat{\chi})\right\|/\left\|Y\right\|=8\%$, $\left\|\left(Y-\hat{Y}_S\right)\right\|/\left\|Y\right\|=8\%$			
$ZZ_1+ZZ_2=105Kg$, $F_{v1}+F_{v2}=202Ns/m$, $F_{c1}+F_{c2}=20.4N$			

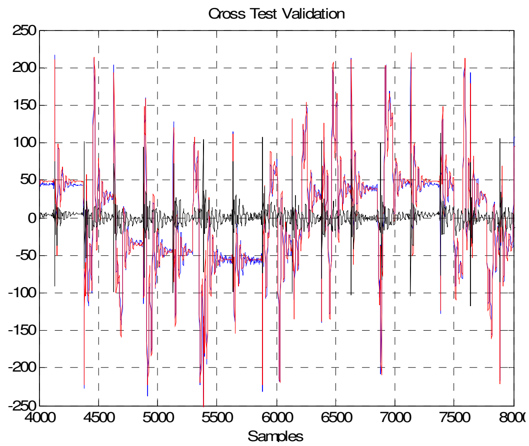

Fig. 4. Cross test validation with IDIM method. Blue: measurement, Red: simulated torque, Black: error.

TABLE 3: DIDIM IDENTIFIED VALUES AFTER 10 ITERATIONS

Parameter	$\hat{\chi}_j$	$2*\sigma_{\hat{\chi}_j}$	$100*\left\|\sigma_{\hat{\chi}_j}/\hat{\chi}_j\right\|$
ZZ_1	69.6	0.18	0.13
F_{v1}	127.0	1.86	0.73
F_{c1}	10.0	0.45	2.25
K_{12}	$8.1\ 10^5$	$3.0\ 10^3$	0.18
F_{v12}	136.0	35.0	12.86
ZZ_2	35.5	0.19	0.26
F_{v2}	76.0	1.67	1.09
F_{c2}	10.0	0.15	0.75
Estimated natural frequency: 29.0Hz			
$\left\|(Y-\hat{Y}_S)\right\|/\left\|Y\right\|=9\%$			
$ZZ_1+ZZ_2=105.1Kg$, $F_{v1}+F_{v2}=203Ns/m$, $F_{c1}+F_{c2}=20.0N$			

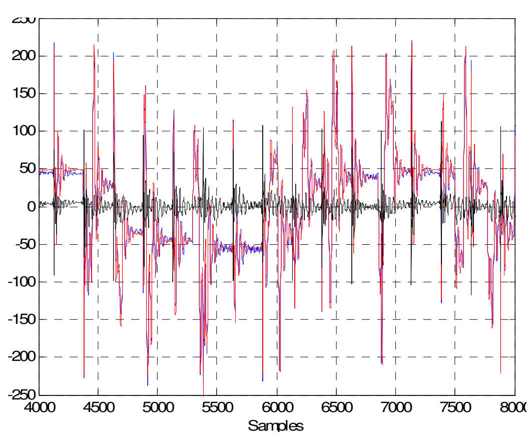

Fig. 5. Direct validation with DIDIM method. Blue: measurement, Red: simulated torque, Black: error.

The parameter F_{v12} has no influence on the dynamics. It posses large standard relative deviation compared with others and when removed from the flexible dynamic model, the norm of the residue and the identified values of the other parameters do not vary significantly (less than 1%).

The standard deviations obtained with DIDIM are slightly different from those obtained with IDIM. This is due to the fact that the observation matrix is built with simulated data instead of measured one as stated in section IV.A. Hence, W_S is perfectly noise free compared with W .

D. *Experimental results with an additional mass of 10Kg on the load*

Now, as a final test, IDIM and DIDIM are performed while an extra mass of 10Kg is added on the load. If identification methods are well designed and accurate enough, variations close to 10Kg must be observed on ZZ_2 whereas insignificant variations must be observed on the other parameters. The estimated values and natural frequency ω_n obtained with IDIM are given in Table 4. The relative norm of the residue and the relative norm of the error between the measured torque and the simulated one are added. The results obtained with DIDIM are given in Table 5 The algorithm converges after 25 iterations. The variations observed on the estimations are given in Table 6.

With IDIM and DIDIM, the variations observed on ZZ_2 are close to 10Kg whereas the variations observed on the other parameters are practically insignificant (excepted for F_{v12} but it has no influence on the dynamic model). The experimental variations can not fit perfectly the theoretical expected one because of noises and experiment conditions.

TABLE 4: IDIM IDENTIFIED VALUES WITH ADDITIONAL MASS

Parameter	$\hat{\chi}_j$	$2*\sigma_{\hat{\chi}_j}$	$100*\left\|\sigma_{\hat{\chi}_j}/\hat{\chi}_j\right\|$
ZZ_1	70.1	0.22	0.15
F_{v1}	95.0	1.90	1.0
F_{c1}	10.0	0.46	2.3
K_{12}	$8.2\ 10^5$	$3.0\ 10^3$	0.18
F_{v12}	210.0	40.0	9.5
ZZ_2	45.0	0.20	0.22
F_{v2}	110.0	1.67	0.76
F_{c2}	10.0	0.16	0.80
Estimated natural frequency: 27.0Hz			
$\left\|(Y-W\hat{\chi})\right\|/\left\|Y\right\|=8\%$, $\left\|(Y-\hat{Y}_S)\right\|/\left\|Y\right\|=8\%$			
$ZZ_1+ZZ_2=115.1Kg$, $F_{v1}+F_{v2}=205Ns/m$, $F_{c1}+F_{c2}=20.0N$			

TABLE 5: DIDM IDENTIFIED WITH ADDITIONAL MASS

Parameter	$\hat{\chi}_j$	$2*\sigma_{\hat{\chi}_j}$	$100*\left\|\sigma_{\hat{\chi}_j}/\hat{\chi}_j\right\|$
ZZ_1	68.5	0.20	0.14
F_{v1}	128.0	1.90	0.74
F_{c1}	11.0	0.45	2.0
K_{12}	$8.2\ 10^5$	$3.0\ 10^3$	0.18
F_{v12}	50.0	20.00	20.0
ZZ_2	45.7	0.18	0.24
F_{v2}	80.0	1.67	1.04
F_{c2}	10.0	0.15	0.75
Estimated natural frequency: 27.0Hz			
$\left\|(Y-\hat{Y}_S)\right\|/\left\|Y\right\|=9\%$			
$ZZ_1+ZZ_2=114.2Kg$, $F_{v1}+F_{v2}=208Ns/m$, $F_{c1}+F_{c2}=21.0N$			

TABLE 6: VARIATIONS OF ESTIMATIONS

Parameter	$\hat{\chi}_j$: IDIM	$\hat{\chi}_j$: DIDIM
ΔZZ_1	**-0.2**	**-1.1**
ΔF_{v1}	3.0	1.0
ΔF_{c1}	0.0	-1.0
ΔK_{12}	**$0.1\ 10^5$**	**$-0.1\ 10^5$**
ΔF_{v12}	84.0	-86.0
ΔZZ_2	**9.8**	**10.2**
ΔF_{v2}	0.0	4.0
ΔF_{c2}	-0.4	0

TABLE 7: RELATIVE ERRORS BETWEEN IDIM AND DIDIM

Parameter	First test	Second test
$\%e(ZZ_1)$	1.0%	2.3%
$\%e(F_{v1})$	38.0%	35.0%
$\%e(F_{c1})$	0.0%	0.0%
$\%e(K_{12})$	1.28%	0.0%
$\%e(F_{v12})$	9.0%	76.0%
$\%e(ZZ_2)$	2.0%	1.6%
$\%e(F_{v2})$	31.0%	27.3%
$\%e(F_{c2})$	4.0%	0.0%

Direct and cross test validations have been performed. As done for the previous experiments, cross test validations consist in simulating the EMPS. The results are very close to those illustrated Fig. 4.

The experimental results prove that we can identify joint stiffness with only one measurement, the actual motor force/torque. The results presented along this paper have shown the effectiveness of our approach. Indeed, the results obtained with DIDIM are comparable with those obtained with IDIM. Remember that three measurements are used to perform IDIM: motor torque, motor and load positions.

VI. CONCLUSION

This paper has described a methodology to identify joint stiffness from only actual force/torque data. To make it possible, the DIDIM method previously validated on a 6 DOF rigid robot [18] has been extended to flexible systems. To highlight the effectiveness of our approach, results obtained with DIDIM were compared with those obtained with IDIM performed with three measurements (actual force/torque data, motor and load positions). The experimental results show that DIDIM results are comparable with IDIM results. This is quite remarkable.

Future works concern the use of DIDIM method to identify a multi DOF robot possessing joint flexibilities. They concern also the calculation of the optimal solution. At this time, the algorithm converges slowly (25 iterations). Others non linear programming optimizers will be analyzed and tested.

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