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A comparison between direct and indirect dynamic parameter identification methods in industrial robots

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SUMMARY

The estimation of dynamic parameters in mechanical systems constitutes an issue of crucial importance both for inverse dynamics based control strategies and dynamic simulation applications where high accuracy is required. The identification procedures can be classified in two main groups: indirect and direct procedures. The first ones act sequentially in several steps in each of them parameters of different nature (basically friction and inertial parameters) are identified by means of specifically designed experiments, while the direct procedures allow the identification of all parameters defining de dynamic model in a single stage. In this paper, the implementation and comparison of an indirect and a direct identification procedures on an industrial robot provided with an open control architecture is addressed.

KEYWORDS: Dynamic parameter identification; Gibbs-Appell equations; Friction modelling.

I. INTRODUCTION

An accurate identification of the constant physical parameters (fundamentally, inertial and friction parameters), which appear in the equations defining the dynamic behavior of the robotic systems, is essential both for the implementation of advanced control schemes and for the dynamic simulation of such mechanical systems. Therefore, since the middle 80's until now, several methods have been proposed for the identification of these physical parameters, especially in industrial robots with open-loop kinematic configuration. A first classification can be established between the so-called integral and differential methods. The first ones are based on the Energy Theorem and require information about generalized forces, positions and velocities. The second ones start from the equation of motion expressed as an inverse dynamic problem and, hence, also require information about the generalized accelerations. Prüfer et al.[1] describe several advantages that make differential methods clearly superior in comparison with integral methods. Therefore, only identification methods based differential models will be considered in the following.

Identification methods based in the differential model can be classified into two main groups:

– Indirect Methods
– Direct Methods

The identification process in the indirect methods is performed sequentially in multiple steps. At each individual one, a subset of the model parameters is identified from various special motions designed in order to excite it. These special motions consist often of simple motions of one or two joints at the same time which can be generated by the standard control unit of any industrial robot. Examples of such identification scheme, can be namely found in Atkeson et al.,[2] Olsen and Bekey,[3] Gautier and Presse,[4] Lin,[5] Otani and Kakizaki,[6] Grotjahn et al.[7] Among the advantages of the indirect methods, the lower complexity of the model, and hence a lower number of parameters to be identified at each one of the steps can be cited, which generally implies a better numerical conditioning of the problem. Additionally, a separate identification of the friction terms of the dynamic model allows the use of motions specifically designed for the identification of the particular friction model being considered. The main drawbacks of indirect identification approaches, as far as the accuracy of the identified parameters is concerned, lie, on one side, on the fact that eventual errors in the results are propagated from one step to the next and, on the other side, on the variability of the friction phenomena through the different steps of the identification process, which supposes an additional error source which could affect the identification of the rest of model parameters (see Khalil and Dombre).[8]

The direct identification methods of Armstrong,[9] Gautier and Khalil,[10] Presse and Gautier,[11] Swevers et al.,[12] Swevers et al.[13] and Calafiore et al.,[14] perform the determination of the totality of the parameters defining the dynamic model of the mechanical system in a single step. In order that the different dynamic parameters of the model are sufficiently excited, the robot motion must be much more accurately designed. This can be namely achieved through the optimization of the robot trajectory according to certain optimality criteria. This identification scheme presents the advantage of being much less time consuming than the indirect approach, as only one single measurement is required

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in order to proceed to the identification of the whole model, hence avoiding the necessity to carry out a large set of experiments with individual special motions. Additionally, as all base parameters are identified in a single step, also the error propagation associated to sequential identification approaches is avoided. Nevertheless, as the complexity of the model to be identified increases, it becomes more difficult to obtain a trajectory which ensures a proper numerical conditioning of the identification problem, which could result in an increase of the uncertainty of the identified parameters.

In this work, two implementations of the direct and the indirect identification schemes, respectively, are considered, and some experimental results are provided which compare the accuracy attained with each of them and show some practical aspects related to their application to an industrial robot. The proposed indirect approach operates in two succeive steps. The first one is intended to estimate the friction model parameters as accurately as possible, starting from a set of simple motions following a procedure similar to the one described in Grotjahn et al.[7] The model gravity parameters are identified in this step in conjunction with the friction parameters so as to allow the application of asymmetric friction models. In the second step of the identification process, the remaining parameters of the model are identified from a single trajectory motion. The direct identification approach proposed in this work is essentially based on Gautier,[15] although the optimized trajectories have been parameterized as finite Fourier series, as described in Swevers et al.[16]

In Section II, the dynamic model on which both identification methods are based is presented and some fundamental aspects concerning the indirect and direct identification algorithms are described. In Section III, the experimental environment which has been used is described. It is constituted by a PUMA 560 industrial robot provided with an open control unit (Valera et al.).[17] In Section IV, both methods are compared through the relation between the generalized forces computed by means of the Inverse Dynamic Problem and the measured control actions. The resolution of the Inverse Dynamic Problem considers, in each case, the set of inertial parameters obtained by means of both proposed identification algorithms. Finally, in Section V, conclusions and future works are reported.

II. DESCRIPTION OF THE IDENTIFICATION METHODS

II.1. Dynamic model

Essentially, three issues are addressed in this Subsection: The principle of dynamics considered for the determination of the equations describing the motion of the mechanical system, which will be later expressed in linear form with respect to the parameters to be identified, the complexity level in the modeling of the mechanical system and, finally, the friction model considered at the kinematic joints.

Various dynamic formulations have been applied in the literature in order to obtain the equations of motion constituting a robot dynamic model. Thus, several authors have considered the Newton-Euler formulation: Luh et al.,[18] Atkeson et al.,[2] Olsen and Bekey,[3] Khosla,[19] or the Jourdain principle: Grotjahn et al.,[20] while others have applied the Lagrange formulation: Hollerbach,[21] Ha et al.,[22] Sheu and Walker.[23] In this paper, the Gibbs-Appell equations of motion have been applied to develop a dynamic model for robot manipulators. The Gibbs-Appell equations constitute, despite their rare use in Robotics, one of the most simple formulations of dynamics equations and possess some other advantages (Prüfer et al.,[1] Mata et al.[24]). At this respect, it must be noticed, on the one hand, the convenience of the inclusion of the actuators in the dynamic model underlying in the process given the influence that these elements exert on the behavior of the robot type being considered. In the other hand, the Gibbs-Appell formulation is particularly suitable for the inclusion of the actuators in the dynamic model of the robot.

As for the friction model considered, both the direct and the indirect identification procedures establish the constraint to consider exclusively friction models linear in the parameters to be identified. This aspect will become obvious when the identification methods to be compared are described.

Given that the type of industrial robot on which the experimental phase will be carried out, from now on mechanical systems with open-loop kinematical structure and provided exclusively with revolute joints will be considered. The local reference system assignation for links, $\{O_i - X_i Y_i Z_i\}$, and actuators, stators $\{O_{Mi} - X_{Mi} Y_{Mi} Z_{Mi}\}$ and rotors $\{O_{Ri} - X_{Ri} Y_{Ri} Z_{Ri}\}$, is performed according to the Denavit-Hartenberg convention, as shown in Fig. 1.

The Gibbs-Appell dynamic equations are derived from the Gibbs function, also known as the energy of accelerations. Considering a reference system located on the i-th link, the Gibbs function for this i-th rigid body of a given mechanical system is given by:

$$G_i = \frac{1}{2} m_i \left({}^i\ddot{\vec{r}}_{G_i}\right)^T \cdot {}^i\ddot{\vec{r}}_{G_i} + \frac{1}{2} \left({}^i\dot{\vec{\omega}}_i\right)^T \cdot {}^i\mathbf{I}_{G_i} \cdot {}^i\dot{\vec{\omega}}_i + \left({}^i\dot{\vec{\omega}}_i\right)^T \cdot \left[{}^i\vec{\omega}_i \times {}^i\mathbf{I}_{G_i} \cdot {}^i\vec{\omega}_i\right] \quad (1)$$

where m_i is the mass of the i-th link, ${}^i\mathbf{I}_{G_i}$ is the central inertia matrix of the i-th link, ${}^i\vec{\omega}_i$ and ${}^i\dot{\vec{\omega}}_i$ are vectors representing the angular velocity and acceleration of the i-th link and ${}^i\ddot{\vec{r}}_{G_i}$ is the center of mass acceleration of the i-th link. All these magnitudes are expressed in the local reference system of the i-th link. For a system consisting of n moving bodies, the Gibbs function of the system would be given by:

$$G = \sum_{i=1}^{n} G_i, \quad i = 1, 2 \cdots n. \quad (2)$$

The Gibbs-Appell equations of motion are obtained by deriving the Gibbs function with respect to the generalized accelerations $\ddot{q}_j$, yielding the generalized inertial forces that compensate the generalized external forces τ_j:

$$\tau_j = \sum_{i=j}^{n} \frac{\partial G_i}{\partial \ddot{q}_j} \quad (j = 1, 2 \cdots n). \quad (3)$$

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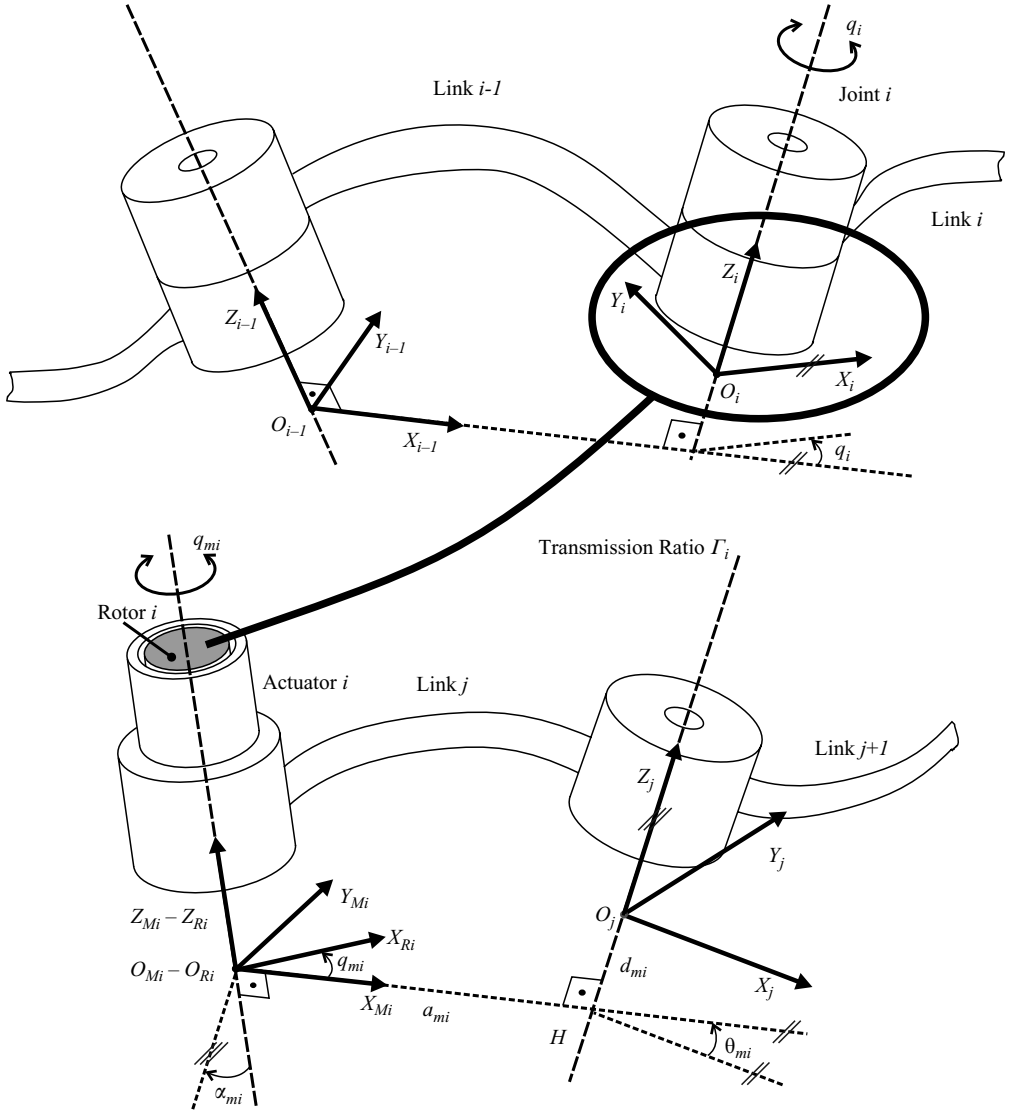


Fig. 1. Link and rotor local coordinate system assignation according to Denavit-Hartenberg notation.

Thus, according to the general dynamic model considering the dynamics of links and rotors as well as joint friction phenomena, the joint torques to be applied by the actuators can be expressed as follows:

$$\tau_k = \tau_{l_k} + \tau_{r_k} + \tau_{f_k} = \underbrace{\sum_{i=1}^{n} \frac{\partial G_{l_i}}{\partial \ddot{q}_k}}_{links} + \underbrace{\sum_{i=1}^{n} \frac{\partial G_{r_i}}{\partial \ddot{q}_k}}_{rotors} + \underbrace{F_{f_k}(\dot{q}_k)}_{friction} \qquad (4)$$

for $k = 1 \ldots n$, where:

- $\tau_k, \tau_{l_k}, \tau_{r_k}, \tau_{f_k}$ denote respectively the total, link, rotor and friction contributions to the k-th joint torque,
- G_{l_i}, G_{r_i} are Gibbs function defined respectively for links and rotors,
- F_{f_k} represents the friction model,
- $q_k, \dot{q}_k, \ddot{q}_k$ are respectively the generalized position, velocity and acceleration and
- n stands for the number of degrees of freedom of the robot manipulator.

This set of equations can be converted into a matrix form, after and adequate linearization, as follows:

$$\vec{\tau} = \mathbf{W}(\vec{q}, \dot{\vec{q}}, \ddot{\vec{q}}) \cdot \vec{\Phi} = [\mathbf{W}_l \,|\, \mathbf{W}_r \,|\, \mathbf{W}_f] \cdot \begin{bmatrix} \vec{\Phi}_l \\ \vec{\Phi}_r \\ \vec{\Phi}_f \end{bmatrix}. \qquad (5)$$

The vector regrouping the dynamic parameters to be identified, $\vec{\Phi}$, has in this case the following form:

$$\begin{aligned} \vec{\Phi}_l &= \left[{}^n\vec{I}_n^T \cdots {}^1\vec{I}_1^T \; m_n \cdot {}^n\vec{r}_{O_nG_n}^T \; m_n \cdots m_1 \cdot {}^1\vec{r}_{O_1G_1}^T \; m_1\right]^T \\ \vec{\Phi}_r &= \left[{}^{r_n}\vec{I}_{r_n}^T \cdots {}^{r_1}\vec{I}_{r_1}^T \; m_{r_n} \cdot {}^{r_n}\vec{r}_{O_{r_n}G_{r_n}}^T \; m_{r_n} \cdots m_{r_1} \cdot {}^{r_1}\vec{r}_{O_{r_1}G_{r_1}}^T \; m_{r_1}\right]^T \\ \vec{\Phi}_f &= \left[Fv_n^+ \; Fc_n^+ \; Fv_n^- \; Fc_n^- \cdots Fv_1^+ \; Fc_1^+ \; Fv_1^- \; Fc_1^-\right]^T \end{aligned} \qquad (6)$$

where:
$Fv_i^+ \; Fc_i^+ \; Fv_i^- \; Fc_i^-$ are the viscous and Coulomb friction coefficients.

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${}^{i}\vec{I}_i, {}^{r_i}\vec{I}_{r_i}$ are vectors regrouping the different terms of the corresponding inertia tensors ${}^{i}\mathbf{I}_{O_i}, {}^{r_i}\mathbf{I}_{O_{r_i}}$ of the i-th link/rotor expressed with respect to the origin of the local coordinate system of the i-th link/rotor, respectively. They have the following form:

$$ {}^{i}\mathbf{I}_{O_i} = \begin{bmatrix} {}^{i}I_{O_{xx_i}} & {}^{i}I_{O_{xy_i}} & {}^{i}I_{O_{xz_i}} \\ {}^{i}I_{O_{xy_i}} & {}^{i}I_{O_{yy_i}} & {}^{i}I_{O_{yz_i}} \\ {}^{i}I_{O_{xz_i}} & {}^{i}I_{O_{yz_i}} & {}^{i}I_{O_{zz_i}} \end{bmatrix} $$

$$ {}^{i}\vec{I}_i = \left[{}^{i}I_{O_{xx_i}} \; {}^{i}I_{O_{xy_i}} \; {}^{i}I_{O_{xz_i}} \; {}^{i}I_{O_{yy_i}} \; {}^{i}I_{O_{yz_i}} \; {}^{i}I_{O_{zz_i}} \right]^T \qquad (7) $$

and analogously for ${}^{r_i}\vec{I}_{r_i}$ and ${}^{r_i}\mathbf{I}_{O_{r_i}}$.

II.2. Direct identification method

Starting from the dynamic equations of motion in linear form with respect to the dynamic parameters to be identified (5), the observation matrix $\mathbf{W}_i$, which consists of as many rows as the degrees of freedom of the manipulator and as many columns as the number of dynamic parameters in the model to be identified, is obtained for each one of the $i = 1 \,..\, m$ robot configurations considered:

$$ \vec{\tau}_i = \mathbf{W}_i \cdot \vec{\Phi}. \qquad (8) $$

The next step consists on assembling the latter matrices for the m configurations. The resultant matrix constitutes the observation matrix of the system for the considered set of configurations. In the same manner, a vector is built by assembling the vectors of generalized forces, i.e. torque vectors, corresponding to each one of these configurations. Thus, the equation system defined by the following expression is obtained:

$$ {}^{a}\vec{\tau} = {}^{a}\mathbf{W} \cdot \vec{\Phi} \qquad (9) $$

where:

$$ {}^{a}\vec{\tau} = \begin{bmatrix} \vec{\tau}_1 \\ \vdots \\ \vec{\tau}_m \end{bmatrix} \quad {}^{a}\mathbf{W} = \begin{bmatrix} {}^{a}W_1 \\ \vdots \\ {}^{a}W_m \end{bmatrix}. \qquad (10) $$

This linear system can be reduced to a full rank linear equation system, where only the base parameters of the model independently determining the dynamic behavior of the system appear. This yields:

$$ {}^{a}\vec{\tau} = {}^{a}\mathbf{W}_B \cdot \vec{\Phi}_B. \qquad (11) $$

The number of configurations m must be chosen so that the number of rows in the observation matrix is greater than the number of columns, hence obtaining an overdetermined linear system. This system is commonly solved by means of the Least Squares Method (LSM).

In order to minimize the effect of measurement noise on the identified parameters, the obtained observation matrix must have a reduced condition number, as well as an adequate numeric equilibration. The condition number of the observation matrix depends on the trajectory used to perform the identification and can therefore only be improved by designing this trajectory in such a way that it sufficiently excites the parameters to be identified. As pointed out in Presse and Gautier,[11] even for reduced condition numbers, measurement errors can considerably affect the results if the observation matrix is not properly numerically equilibrated. It must be noticed that the inclusion of actuators and friction modeling in the model structure increases the condition number of the observation matrix. A LAPACK routine has been applied for the equilibration of the observation matrix.

When the trajectory applied to perform the identification is periodic, it is possible to considerably diminish the effect of measurement noise by averaging the measurements corresponding to several trajectory periods. Thus, the accuracy of the obtained results can be significantly improved without increasing the size of the observation matrix and, consequently, the size of the equation system to be solved.

II.3. Indirect identification method

The equation system applied in the last Subsection for the direct identification algorithm can be decomposed, attending to the nature of the dynamic effect implied, in three parts as follows:

$$ \vec{\tau}_i = \mathbf{W}_{Bi} \cdot \vec{\Phi}_B \equiv [\vec{\tau}_{Ii} + \vec{\tau}_{Gi} + \vec{\tau}_{Fi}] $$

$$ = [\, \mathbf{W}_{BIi} \; \mathbf{W}_{BGi} \; \mathbf{W}_{BFi} \,] \cdot \begin{bmatrix} \vec{\Phi}_{BI} \\ \vec{\Phi}_{BG} \\ \vec{\Phi}_{BF} \end{bmatrix} \qquad (12) $$

where $\vec{\Phi}_{BI}$, $\vec{\Phi}_{BG}$ and $\vec{\Phi}_{BF}$ are, respectively, the base parameters associated with the elements of the inertia matrix, the gravity and the friction parameters. In their turn, $\mathbf{W}_{BIi}$, $\mathbf{W}_{BGi}$, $\mathbf{W}_{BFi}$ and $\vec{\tau}_{Ii}$, $\vec{\tau}_{Gi}$, $\vec{\tau}_{Fi}$ are, respectively, the corresponding parts of the observation matrix and the vector of generalized forces of the system.

The identification of the friction coefficients of each joint is performed separately and stepwise from the last to the first joint of the manipulator. At each step, only one joint is moved with a constant velocity, while the others are kept at rest. The gravity parameters affecting the motion of the corresponding joint are also identified together with the friction coefficients. An observation matrix with gravity and friction information, as well as a vector of joint torque measurements, are constructed from a set of configurations of the manipulator and the constituted linear equation system is subsequently solved by means of a standard LSM algorithm. A previous optimization of this set of configurations can eventually be taken into account in order to ensure a low condition number for the observation matrices, especially when introducing more complex friction models with a larger number of parameters to be identified.

The motion of a joint has a trapezoidal velocity profile, so that torque measurements can be taken from the constant velocity region of the motion, where the joint reaches the desired configuration. This trapezoidal profile is repeated for a set of different constant velocity values both in the positive and in the negative sense of rotation, so obtaining for each one of such experiments a pair of torque-velocity

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measurements, which allows obtaining the well-known torque-velocity friction curve corresponding to each joint and configuration. The combination of the measurements obtained for all constant velocity values and robot arm configurations allows the determination of an observation matrix and a torque measurement vector which constitute the equation system from which the friction model coefficients and the gravity parameters corresponding to the moving joint can be identified.

The base parameters accounting for the gravity torque for each joint can be determined by means of a numerical analysis similarly as performed for the determination of the base parameters of the dynamic model. The identification procedure starts with the motion of the last link and follows until the first link. At each step, the gravity parameters identified in previous steps are used to compensate the measured torque, so that only the new parameters corresponding to the current moving link are identified, which reduces the size of the observation matrix and hence improves the numerical conditioning of the equation system to be solved. For the rigid link dynamic model, only two gravity parameters are identified at each step in addition to the friction model coefficients.

The second step of the identification of the robot manipulator dynamic model is quite similar to the direct identification approach. Joint angular position and torque measurements are obtained from the robot, which must describe an optimized exciting trajectory. The contribution to the joint torque due to friction and gravity is first calculated by means of the base parameters estimated in the last step and subsequently used to correct the values of the measured torques. Hence, an equation system is obtained for each robot configuration considered, which can be expressed as:

$$\vec{\tau}_{Ii} = \mathbf{W}_{Ii} \cdot \vec{\Phi}_I \tag{13}$$

where $\vec{\tau}_{Ii}$ is the corrected vector of torque measurements and $\mathbf{W}_{Ii}$ is the observation matrix corresponding to the reduced model not considering the gravity and friction contributions. The torque vector and the observation matrix are analogously appended for the m considered configurations and reduced to the model base parameters in order to assemble an equation system in the form:

$$^{a}\vec{\tau}_I = {}^{a}\mathbf{W}_{BI} \cdot \vec{\Phi}_{BI} \tag{14}$$

where:

$$^{a}\vec{\tau}_I = \begin{bmatrix} \vec{\tau}_{I1} \\ \vdots \\ \vec{\tau}_{Im} \end{bmatrix} \quad {}^{a}\mathbf{W}_{BI} = \begin{bmatrix} \mathbf{W}_{BI1} \\ \vdots \\ \mathbf{W}_{BIm} \end{bmatrix}. \tag{15}$$

As in the direct identification approach, the number of configurations m must be selected so as to obtain an overdetermined equation system. Finally, the latter equation system is solved in order to identify the rest of the base parameters not appearing in the already estimated friction and gravity models described above.

II.4. Friction modeling

Four different static friction models, using the nomenclature stated in Olsson et al.,[25] have been considered in order to account for the friction at the joints, namely: a symmetric classical model F2 with a dry and a viscous friction term, a symmetric model F3 also including a third term proportional to the square root of the velocity, as described in Grotjahn et al.,[7] Grotjahn et al.,[20] and the respective asymmetric models F4 and F6. The expressions corresponding to these models are shown in Eqs. 16, 17, 18 and 19, respectively, where $\dot{q}_i$ is the generalized velocity corresponding to the i-th joint.

$$\tau_{f_i} = F_{i_1} \cdot \dot{q}_i + F_{i_2} \cdot sign(\dot{q}_i) \tag{16}$$

$$\tau_{f_i} = F_{i_1} \dot{q}_i + F_{i_2} sign(\dot{q}_i) + F_{i_3} \dot{q}_i^{1/3} \tag{17}$$

$$\tau_{f_i} = \begin{cases} F_{i_1} \cdot \dot{q}_i + F_{i_2} & \dot{q}_i > 0 \\ F_{i_3} \cdot \dot{q}_i - F_{i_4} & \dot{q}_i < 0 \end{cases} \tag{18}$$

$$\tau_{f_i} = \begin{cases} F_{i_1} \cdot \dot{q}_i + F_{i_2} + F_{i_3} \cdot \dot{q}_i^{1/3} & \dot{q}_i > 0 \\ F_{i_4} \cdot \dot{q}_i - F_{i_5} + F_{i_6} \cdot \dot{q}_i^{1/3} & \dot{q}_i < 0 \end{cases} \tag{19}$$

III. EXPERIMENTAL BENCHMARK

The indirect and direct methods presented in the preceding Sections will be applied to the identification of the inertial and friction parameters of a PUMA 560 industrial robot. This robot has been provided with an totally open control architecture (Valera et al.)[17] in which the original control unit has been replaced with a PC provided with the corresponding data acquisition cards. The angular position measurements are obtained by means of incremental encoders, while the joint torques are estimated starting from the control actions provided by the control algorithm. The relation between these control actions and the currents supplied to the motors, as well as between the latter and the generated actuator torques, can be assumed to be linearly proportional and constant for the DC motors used as actuators under the kinematical constraints determined for the current application. The angular position data can be fitted using the LSM by means of an analytical function of the same type as the one used to parameterize the identification trajectory. This allows, as an advantage of the use of parameterized trajectories, the calculation of joint angular velocities and accelerations by deriving the function corresponding to the angular position analitically, thus avoiding the drawbacks related with numerical differenciation of measurement data and the high frequency noise amplification that it implies.

As described in Sections II.2 and II.3, the indirect and direct identification methods build the corresponding observation matrices starting from a sufficient number of data values measured from previously designed robot trajectories. The optimized trajectory applied to perform the required identifications has been parameterized as a finite Fourier series according to the approach described in Swevers et al.[12,13,16] As for the optimization procedure, the condition number of the observation matrix has been considered as

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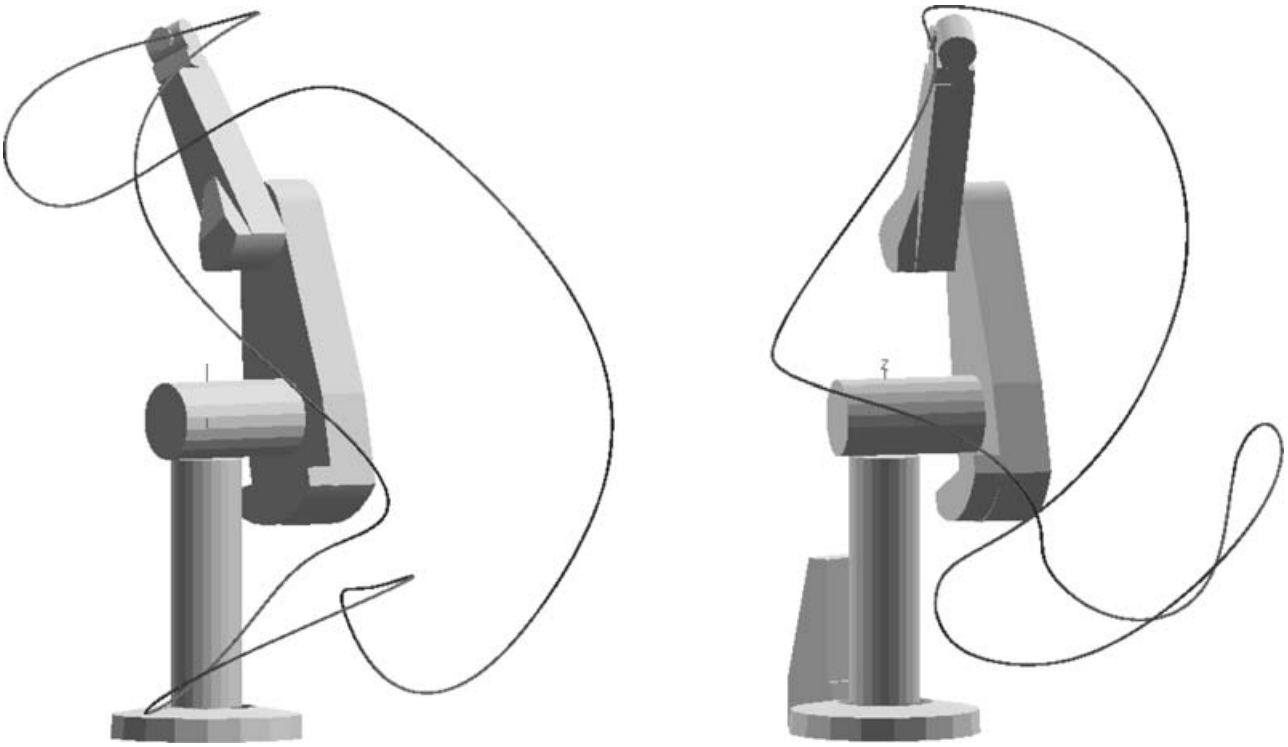


Fig. 2. End-effector paths corresponding to trajectory used in the identification experiments (TF1) and in the test phase (TF2).

the objective function to be minimized and the pertinent joint and working space kinematic constraints related to the actual robot and its workspace have been imposed. A Sequential Quadratic Programming optimization algorithm has been applied. The end effector paths corresponding to the finite Fourier series trajectory used in the identification experiments (TF1) and in the test phase (TF2) are shown in Fig. 2.

The indirect identification approach is performed, as detailed in Section II, in two separate steps. In the first step, constant velocity values and robot arm configurations were determined empirically in order to achieve low condition numbers for the resultant observation matrices. The application of an optimization process to find optimal configurations was judged not to be necessary due to the relatively low condition numbers that are generally obtained. Thus, at each robot configuration, the active joint is moved for a set of constant velocity values in both senses of rotation following a velocity trapezoidal profile as seen in Fig. 3.

Data samples corresponding to the proximity of the theoretical configuration in a 10% of the total amplitud of the joint motion, which are marked in Fig. 3 as points in the graphs, are averaged in order to diminish the influence of eventual measurement errors in the determination of the values of angular position, angular velocity and torque for the measurement. The obtained angular velocity and torque pairs allow to build the characteristic joint friction curve for a certain configuration as shown in Fig. 4.

The mean values of the root-mean-square (RMS) residuals of the computed torque errors determined for all configurations of each joint are shown in Table I. In this comparison, friction modeling and gravity parameters of the model are being considered, which allows a better judgment of the relative accuracy that can be achieved with each one of the friction models.

Table I. Mean values of the RMS residuals of the computed torque test errors for the indirect friction identification experiment using four different friction models.

	Joint					
	1	2	3	4	5	6
F2	0.52305	0.38388	0.39561	0.11484	0.087597	0.82216
F3	0.52099	0.38311	0.39292	0.11355	0.086139	0.80812
F4	0.40929	0.45539	0.1155	0.11216	0.068484	0.27826
F6	0.40564	0.45169	0.10496	0.11084	0.065814	0.24231

As can be observed, the non-linear model F3 does in principle not significantly improve the accuracy with respect to the F2 model. Except for the second and fourth joints, the use of the asymmetric friction models implies a considerable reduction of the predicted torque errors with respect to the symmetric models. Model F6 introduces only a slight improvement in comparison with the classical model F4. Hence, the use of the assymetric classical model F4 will be considered as a compromise between the simplicity of both model and identification process and the accuracy of the identification results.

IV. COMPARISON OF THE TWO IDENTIFICATION METHODS

In the direct identification approach, all base parameters of the dynamic model are obtained by solving an overdetermined linear system built with data measured from a single trajectory experiment with trajectory TF1, following

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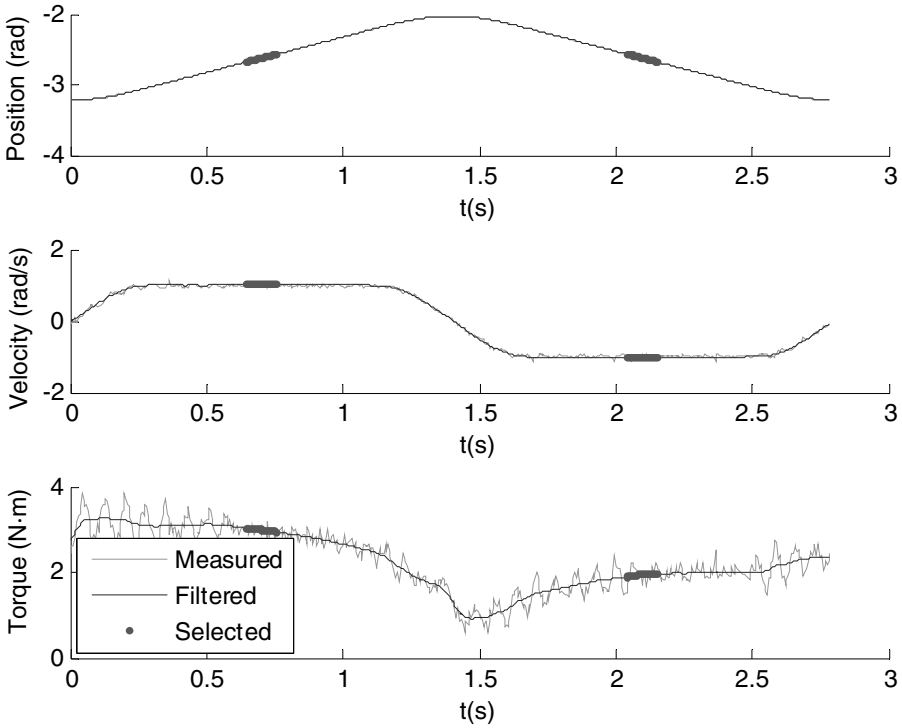


Fig. 3. Example of a velocity trapezoidal profile for the friction identification experiment.

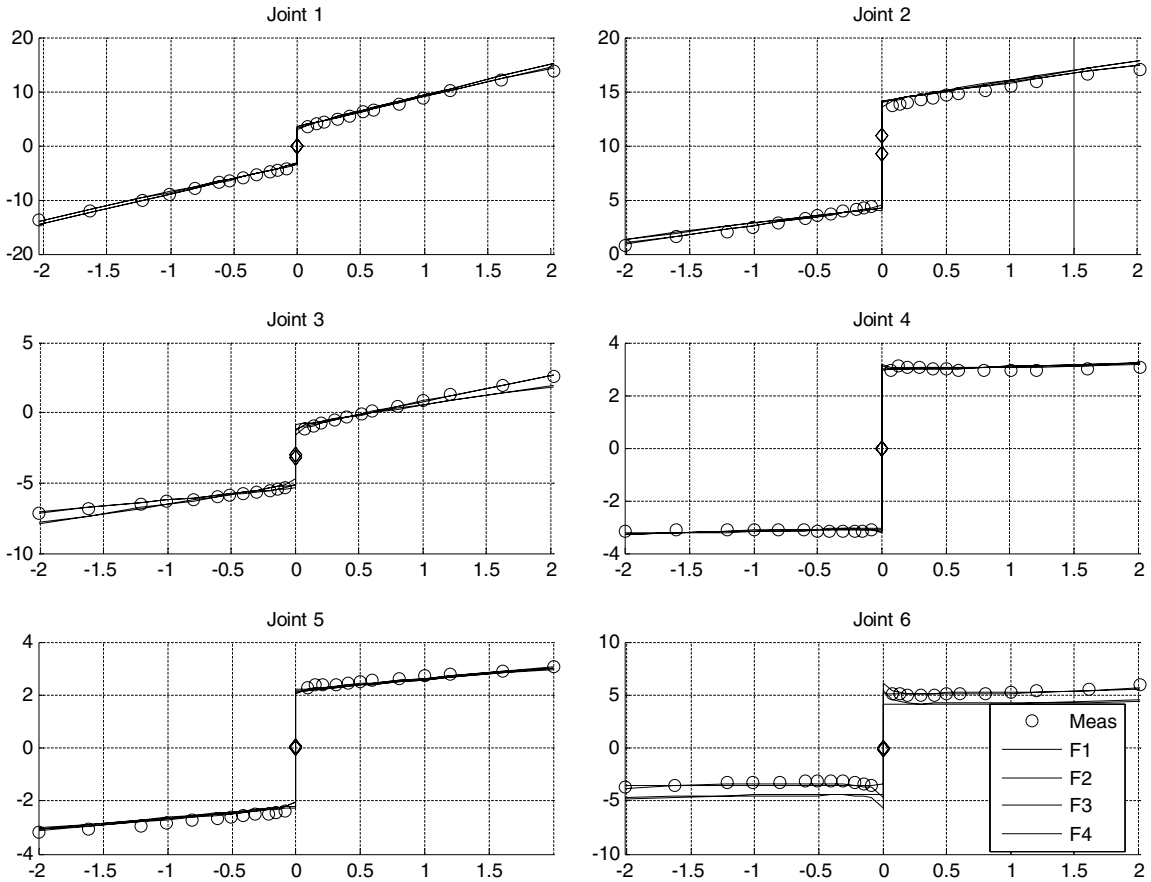


Fig. 4. Comparison of measured and predicted torque for different friction models corresponding to certain configurations of the friction identification experiment in the indirect approach.

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Table II. Base parameters identified for the rigid link dynamic model with friction model F4 using the direct approach.

	Joint					
	1	2	3	4	5	6
Ixx	0	–0.35785	0.051172	–0.05259	0.033371	0.027137
Ixy	0	0.021497	0.16631	0.002676	–0.00522	0.012795
Ixz	0	–0.24795	–0.21942	–0.01965	–0.02437	–0.01617
Iyy	0	0	0	0	0	0
Iyz	0	0.207203	–0.16839	0.004945	–0.02293	0.015996
Izz	1.139638	0.59889	0.1105	0.004035	0.016983	0.030874
mx	0	3.823667	–0.03261	0.003377	–0.00833	0.005467
my	0	–0.14891	–0.80242	0.033391	–0.01672	0.004463
mz	0	0	0	0	0	0
m	0	0	0	0	0	0
fl	6.047542	4.996021	3.108466	2.976105	1.583249	5.098158
f2	12.76186	2.099302	1.251897	0.257472	0.534429	0.232536
f3	5.2298	4.952096	3.127734	2.779865	1.971336	3.22636
f4	11.87085	4.269759	0.46629	0.349379	0.238073	0.324467

Table III. Gravity and friction base parameters identified for friction model F4 with the indirect approach.

	Joint					
	1	2	3	4	5	6
mx	0	3.79590	–0.03752	0.00225	0.00467	–0.00886
my	0	–0.23932	–0.87385	–0.01236	–0.00066	0.00633
fl	3.50090	3.16540	2.05570	2.98530	2.11440	5.08010
f2	5.77580	1.88430	1.91750	0.10782	0.41737	0.19337
f3	3.43530	6.71270	2.14920	3.07330	2.28970	3.47320
f4	5.14210	1.41430	0.88037	0.09297	0.42350	0.04326

the procedure described in Section II. The model base parameters are shown in Table II.

In the case of the proposed indirect method, the friction and gravity base parameters are determined as described in the preceding Section. The corresponding results are shown in Table III.

The gravity and friction parameters identified in the first step are used to compensate the torque measurements for trajectory TF1, which is used in the second step of the identification process to identify the rest of the dynamic model parameters, analogously as described for the direct identification approach. The joint torque due to the effect of inertia is the remaining torque after compensating the friction and gravity contributions in the measured torque.

Table V. Mean values of the RMS residuals of the computed torque test errors with trajectory TF2 for the direct and the indirect identification approaches.

	Joint					
	1	2	3	4	5	6
Direct	2.1333	1.5915	1.0123	1.1178	0.74999	1.2786
Indirect	8.3391	2.9526	1.3162	1.6724	1.2089	1.3867

The dynamic model base parameters obtained in this step of the identification, i.e. the inertia base parameters, can be seen in Table IV.

Following, the results obtained through the direct identification approach, base parameters shown in Table II, and the indirect identification approach, base parameters in Table III and Table IV, are compared, in a first instance, by means of the computed torque test using as test trajectory the finite Fourier series trajectory TF2, which is different from the trajectory used in the identification experiments. Fig. 5 and Fig. 6 show the comparison between measured and predicted torques, while the mean values of the RMS residuals corresponding to the predicted torque errors for each joint can be seen in Table V and Table VI, respectively. As can be observed, the torque predicted using the base parameters identified by means of the direct identification approach is more accurate than the corresponding to the indirect identification approach, specially for the first joint.

Table IV. Inertia base parameters identified in the second step of the indirect identification approach.

	Joint					
	1	2	3	4	5	6
Ixx	0	–0.73238	0.38005	0.057734	–0.10327	0.078296
Ixy	0	0.085947	0.108683	0.200006	0.00844	–0.0055
Ixz	0	–0.86006	0.301183	0.127573	–0.0932	0.010288
Iyy	0	0	0	0	0	0
Iyz	0	0.510905	–0.07133	0.207737	0.14413	–0.00391
Izz	1.571159	0.011705	–0.04949	0.440722	0.185264	0.133328

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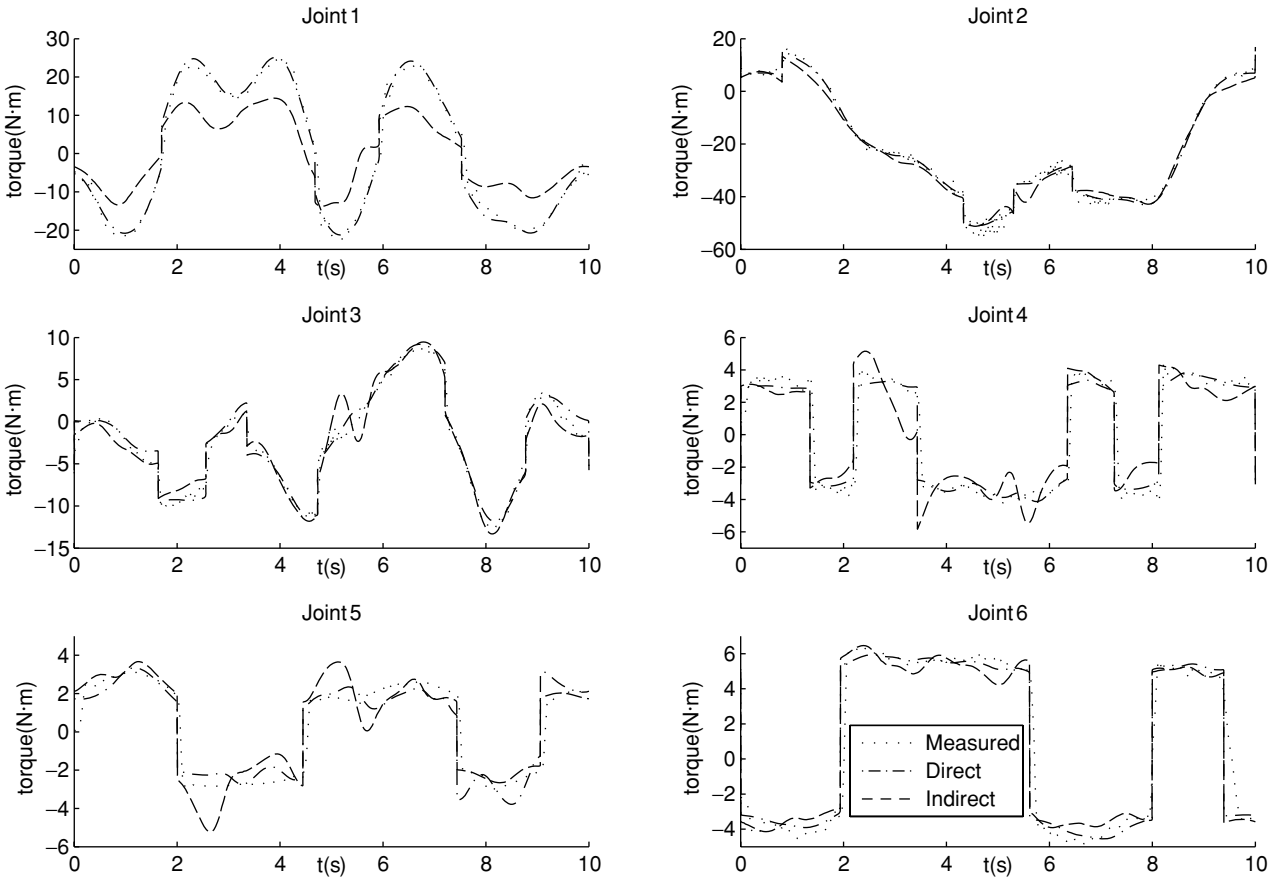


Fig. 5. Computed torque test with trajectory TF2 for the direct and the indirect identification approaches.

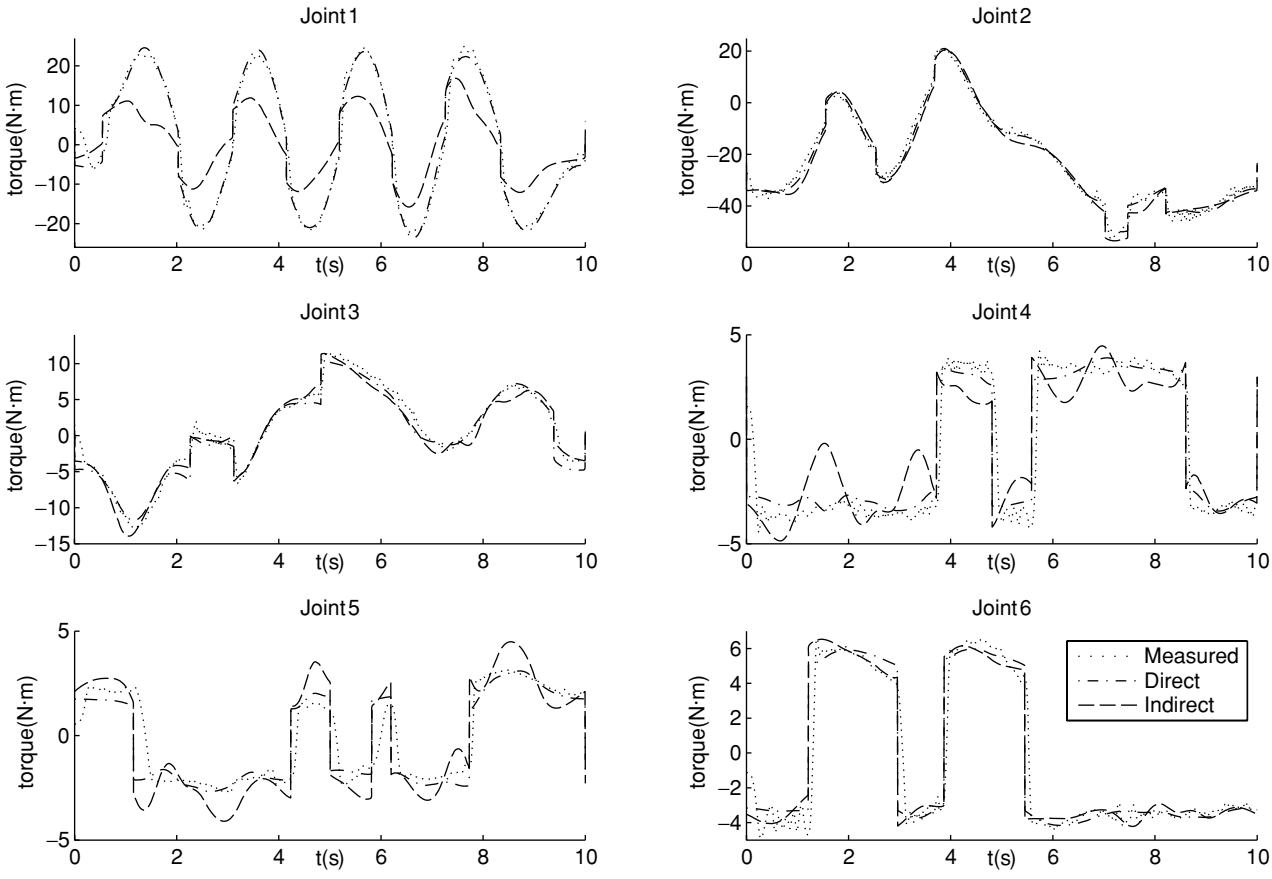


Fig. 6. Computed torque test with trajectory TF3 for the direct and the indirect identification approaches.

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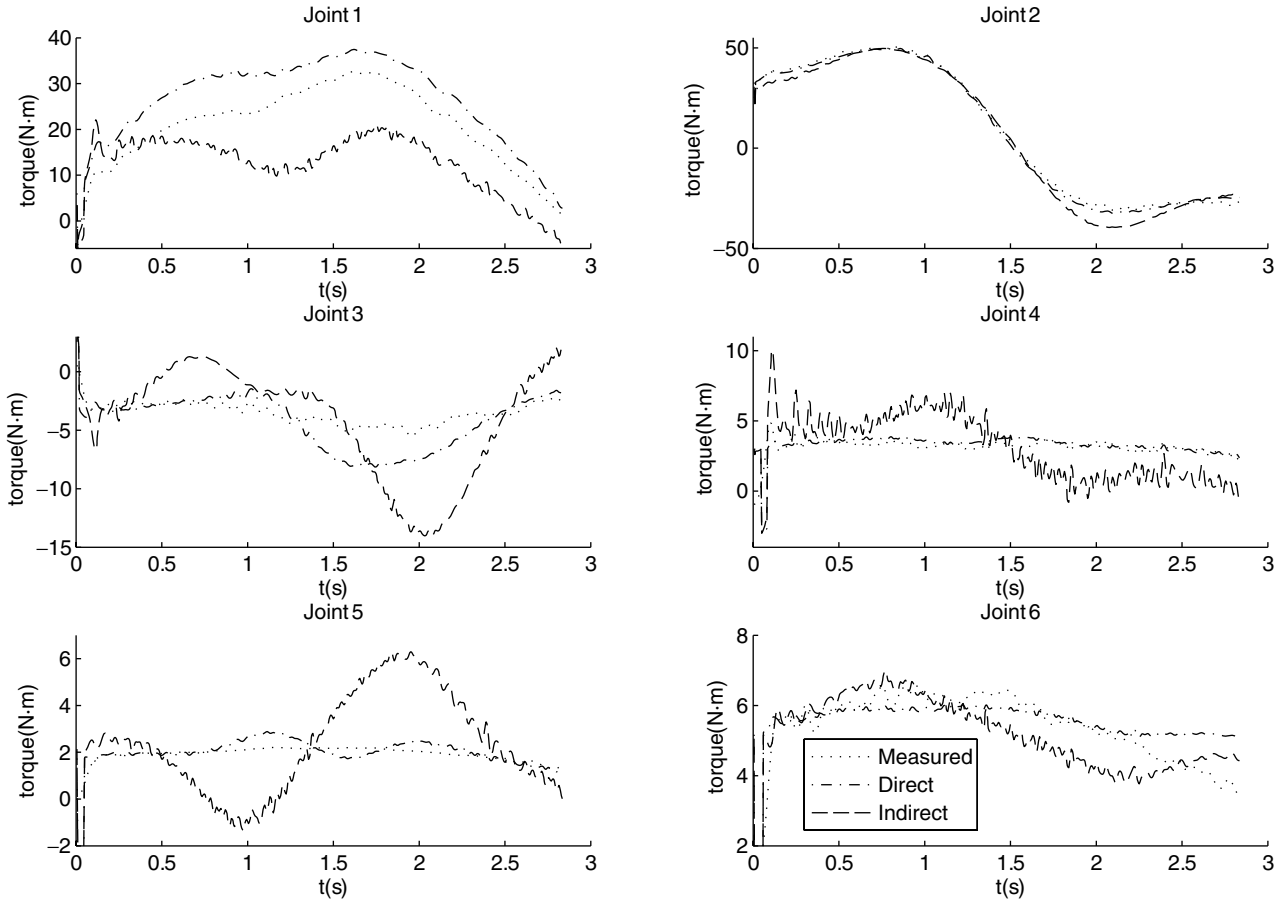


Fig. 7. Computed torque test with cubic spline test trajectory TS1 (1.6 rad/s) for the direct and the indirect identification approaches.

Table VI. Mean values of the RMS residuals of the computed torque test errors with trajectory TF3 for the direct and the indirect identification approaches.

	Joint					
	1	2	3	4	5	6
Direct	2.6951	1.9220	1.2067	1.1843	0.9718	1.4126
Indirect	9.0990	3.0399	1.1514	1.7192	1.3641	1.5549

Table VII. Mean values of the RMS residuals of the computed torque test errors with cubic spline test trajectory TS1 (1.6 rad/s) for the direct and the indirect identification approaches.

	Joint					
	1	2	3	4	5	6
Direct	5.9036	1.6732	1.6794	0.76636	0.39055	0.84671
Indirect	10.089	4.5522	4.0594	2.1778	2.119	0.9531

Table VIII. Mean values of the RMS residuals of the computed torque test errors with cubic spline test trajectory TS2 (0.1 rad/s) for the direct and the indirect identification approaches.

	Joint					
	1	2	3	4	5	6
Direct	3.1455	0.91259	1.0934	0.67207	0.42606	1.0023
Indirect	0.93231	2.178	0.56989	0.68284	0.85507	1.0037

To avoid the similarity of the test trajectory with the identification trajectory, the test is also performed with two cubic spline trajectories, which are representative as they constitute the default type of trajectory used by the standard control of a PUMA 560 robot manipulator. The test is carried out both for a high (TS1) and for a low (TS2) overall angular velocity value. The comparison of measured and predicted torques is shown in Fig. 7 and Fig. 8, while the mean values of the RMS residuals of the predicted torque erros can be seen in Table VII and Table VIII. As can be observed, the indirect approach performs comparatively better at low angular velocities for joints with a higher contribution of friction to the joint torque, specially the first joint. The predicted torque error generally increases with the angular velocity much more rapidly for the indirect identification approach. Thus, for the cubic spline trajectory with a high angular velocity value, the errors become considerably larger for the indirect approach for all joints.

A comparison of the results obtained for the finite Fourier series and the cubic spline test trajectories allows to observe that similar effects appear for high values of joint angular velocities, resulting in a worse accuracy of the predicted torque for the indirect identification approach

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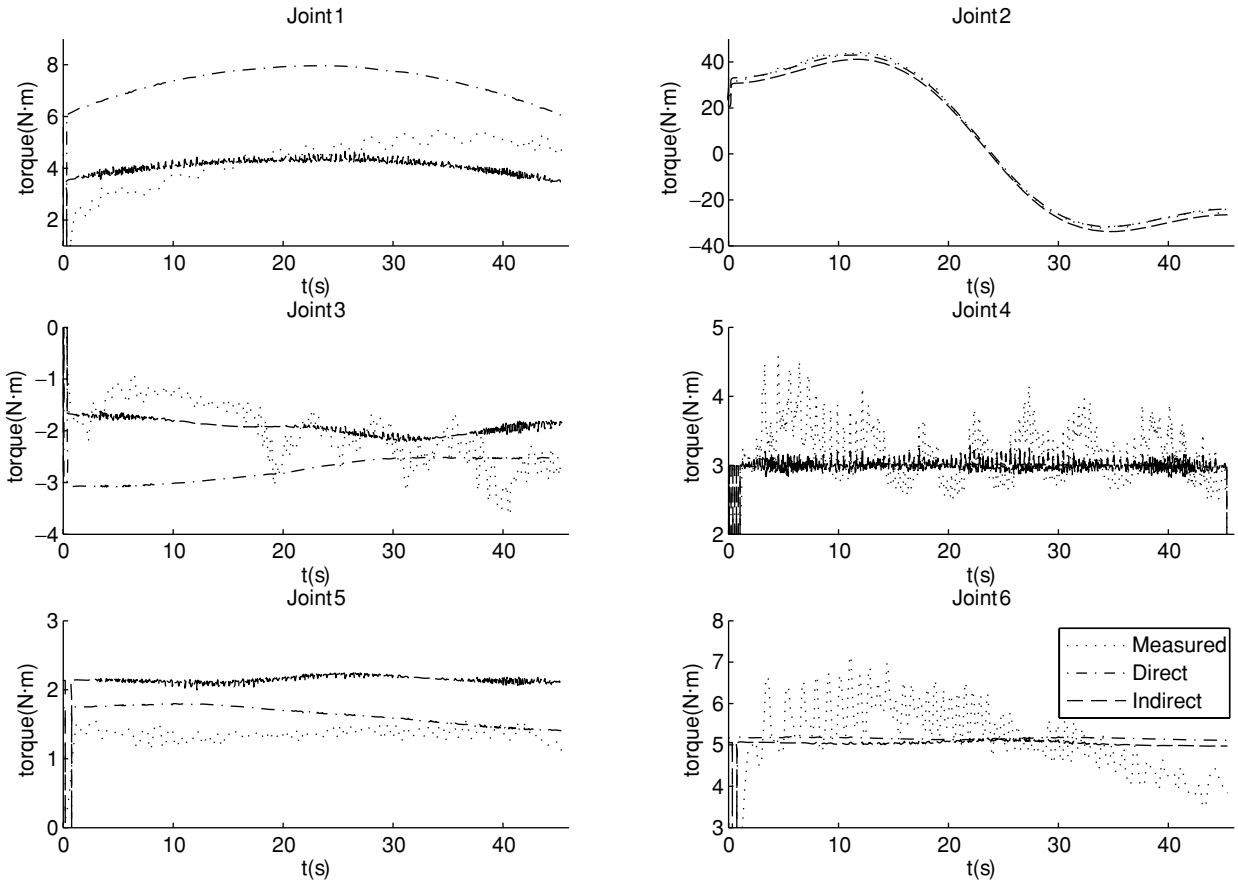


Fig. 8. Computed torque test with cubic spline test trajectory TS2 (0.1 rad/s) for the direct and the indirect identification approaches.

in comparison with the direct approach. For low velocity values, in contrast, the accuracy of the torque predicted by the indirect identification approach is clearly improved and, for some joints, becomes even more accurate than the direct identification approach. This effect becomes specially remarkable for the first joint.

This behavior can be explained considering the type of motions involved in the friction identification experiments for each one of the identification approaches. In the direct approach, friction is identified, simultaneously with the rest of the dynamic model, using measurement data from a finite Fourier series trajectory, for which velocity and acceleration vary constantly in the whole range defined by the robot kinematic bounds. This implies the appearance of joint torque contributions due to the effect of inertia in the moving parts of the robot. On the other hand, in the indirect identification approach, friction is identified using constant velocity simple motions where, furthermore, only one joint moves at a time, so that the absence of inertia effects involved in the joint torques can be reasonably assumed.

Due to the quite different nature of the motions applied in each one of the identification approaches, it seems reasonable to suppose that the torque predicted by a set of identified base parameters will be more accurate for trajectory types providing dynamic conditions similar to the ones present in the robot motions applied in the identification approach used to obtain this base parameter set. This appears to be confirmed by the results obtained from the cubic spline trajectory with low overall joint angular velocity values, in which inertia effects are only slightly excited, hence approaching the dynamic behaviour of the motions used for friction identification in the indirect approach. The pronounced behavior in the case of the first joint could most reliably be attributed to the different mechanical structure of the transmission gears for this joint, particularly due to the presence of a bevel gear. Thus, forces acting on the gear system seem to exert a notable influence on its friction characteristics.

V. CONCLUSIONS

In this work, the issue of industrial robot dynamic parameter identification, considering a direct and an indirect identification approach, has been addressed. The considered dynamic model has been obtained starting from the Gibbs-Appell equations and has been expressed linearly with respect to the parameters to be identified in a straightforward manner. The validity of the proposed identification approaches has been tested by means of experiments on a PUMA 560 robot.

The following conclusions can be extracted after observing the behavior of the direct and the indirect identification

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approaches in the different experimental examples shown in the present work:

- Assuming the limitations of the applied friction modeling, the proposed direct approach is shown as the most reliable so as to minimize the predicted torque errors for the identified dynamic model when applying trajectories with a considerable contribution of the inertial effects, i.e. with high values of the joint angular velocities and accelerations.
- For trajectories with low angular velocity and acceleration values, the indirect approach provides, in general, a more accurate torque prediction for most joints of the manipulator, specially those with a predominant contribution of the friction effects to the joint torque.
- The friction models applied in this work, which are constraint to be linear in the parameters to be identified, seem to be unappropriate in order to model the joint friction phenomena which take place in the PUMA 560 robot manipulator used in the experimental phase of the work, specially in the case of the first joint. A sufficiently accurate and probably mathematically complex friction model would be necessary for a successful practical application of the indrect approach to trajectories with important contributions of inertial effects. Also the friction identification trajectories should be modified, in this case, in order to allow the identification of several static and dynamic friction phenomena arising with the dynamic conditions which appear in general trajectories with varying velocity and acceleration.

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