Dynamic Identification of YuMi ABB Collaborative Robot

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Résumé :

Afin d'améliorer la précision des simulateurs de robots et de développer de nouvelles lois de commande, il est nécessaire d'identifier les paramètres physiques de leur modèle dynamique. Dans cet article, nous proposons une estimation des paramètres dynamiques du robot ABB IRB14000 (YuMi). Une méthode d'identification de base du robot utilisant le modèle dynamique inverse et les moindres carrés est utilisée. Les valeurs numériques sont présentées dans ce document pour aider les chercheurs intéressés à développer et à améliorer les résultats de notre propre étude.

Abstract:

In order to improve the precision of robot simulators and to develop new control laws, it is necessary to identify the physical parameters of their dynamic model. In this paper, we propose an estimation of the dynamic parameters of the robot ABB IRB14000 (YuMi). A basic identification method of the robot using the inverse dynamic model and the least squares is used. Numerical values are presented, in this paper, to help interested researchers to develop and improve the results of our own study.

Keywords: Robot Identification, Dynamic model, YuMi, Optimization.

1 Introduction

In order to develop accurate dynamic models and to implement new control algorithms, the identification of dynamic parameters of manipulator robots has been focused by many researches. System identification in general is related to the construction of models describing the physical process mathematically. Those models are characterized by a structure and by dynamic parameters for which numerical values are unfortunately not fully provided by the manufacturers.

In literature, identification is strongly related to statistical methods, such as the least squares method or the maximum likelihood method which is often applied in the industry. IDM_LS method, generally adopted in robotics, is based on the inverse dynamic model (IDM) and the least squares (LS). This technique has been successfully applied for the experimental identification of robots [1] [2] and is a preliminary step for other off-line or on-line approaches [3] [4]. The output error method (OE) compares the behaviour of the real system with the mathematical model. This model is iteratively modified to optimize parameters, in order to bring the behaviour of the model closer to that of the real robot. The criterion often used is the quadratic norm of the output error. This method can be implemented in open loop or in closed loop (CLOE) [5][6].

[7] proposed a new method of closed-loop output error based on a closed loop simulation of the robot, by minimizing a quadratic error between the actual and simulated joint torques using the robot's direct and inverse dynamic model called DIDIM. This new method has been successfully applied to rigid manipulator robots. A comparison between DIDIM and CLOE was made by [8] and an extension of DIDIM method has been validated for robots with flexible joints in [9].

For systems with few parameters, the Extended Kalman Filter (EKF) was used since the 1980s. The algorithm estimates both the state of the system and the parameters using the direct dynamic model. However, the EKF algorithm is sensitive to initial conditions and the velocities of convergence is very slow [10]. [11] discussed the identification of parametric linear models with continuous time.

In our study, the experimental work was done on the ABB IRB 14000 collaborative robot named YuMi (Fig. 1).

YuMi is the first safe collaborative industrial robot with two 7 DOF (Degree of Freedom) arms. This Dual-arm ABB robot is ideal for assembling small parts with a load capacity of 500g for each arm. It is controlled with the ABB IRC5 control system. The two arms of the robot are the same manipulator of 7 DOF with two different bases. For this reason, it is sufficient to identify the parameters of a single arm.

The first part of this paper presents the kinematic and dynamic model of YuMi robot. The identification method used, the method to optimize identified parameters and the method to calculate the precision of these parameters are described in the second part. In the last part, the experiments carried out to measure and filter the data, the results obtained and the perspectives of this work are presented.

Fig. 1 Robot IRB14000 from ABB (in LCFC lab)

2 Model of Yumi

2.1 Kinematic model of YuMi robot

The modelling of a manipulator robot requires first of all to establish its kinematic model (KM). We therefore opted for the method of Denavit-Hartenberg Modified (DHM) frequently used in robotics.

The DHM parameters for a single-arm of YuMi robot are listed in Table 1 and are used for robot dynamic modeling, using the *SY*MORRO+ software [12].

Those parameters are also used for robot simulator with Peter Corke Toolbox on MATLAB [13].

Table 1. DHM parameters of YuMi dual arm robot

Articulation	α_i (rad)	d_i(cm)	r_i (cm)	θ_i (rad)
1	0	0	16.6	$q_1 - \pi$
2	$\pi/2$	3	0	$q_2 - \pi$
3	$\pi/2$	3	25.15	q_3
4	$-\pi/2$	4.05	0	$q_4 - \pi/2$
5	$-\pi/2$	4.05	26.5	$q_5 + \pi$
6	$-\pi/2$	2.7	0	$q_6 - \pi$
7	$-\pi/2$	2.7	3.6	$q_7 + \pi$

2.2 Dynamic identification model

To obtain the dynamic model of the robot, the most common approaches are the Lagrange method, the Newton-Euler method and the Kane method [14]. The inverse dynamic model of the robot is written in the following form:

$$\Gamma_{\text{mdi}} = \text{IDM}\,(q, \dot{q}\,\ddot{q}, \text{X}) \qquad (1)$$

Where $q, \dot{q}, \ddot{q}, \Gamma_{\text{mdi}}$, are respectively the vectors [7×1] of the positions, velocities, accelerations and joint torques, X being the vector $[\text{N}_p \times 1]$ of the standard dynamic parameters (inertial and friction) of robot (N_p is the number of standard parameters). This model is written in linear form (2) as a function of basic dynamic parameters (called basic inertial). These parameters were calculated analytically with a simple calculation of the robot's mechanical energy [15].

$$\Gamma_{\text{mdi}} = \text{LIDM}(q, \dot{q},\, \ddot{q})\,\chi \qquad (2)$$

The dynamic model of a robot depends on a number of rigid articulation modelling parameters. There are 11 basic inertial parameters for each joint. We can define a vector χ (3) to represent the parameters of inertia of the joint j.

$$[\,XX_j\;\; XY_j\; XZ_j\; YY_j\; YZ_j\; ZZ_j\; MX_j MY_j\; MZ_j M_j Ia_j]^T \qquad (3)$$

where XX, XY, XZ, YY, YZ, ZZ are 6 components of the inertial tensor, MX, MY, MZ are 3 components of the first moment of inertia, M is the joint's mass and I_a is the inertia of the actuator.
For our robot, we have 11 × 7 inertial parameters. Some inertial parameters are grouped together with SYMORO+ software, which helped us reduce the number of inertia parameters from 77 to 50 parameters by eliminating parameters that cannot be identified. Grouped terms have the index R (ZZR1 for example).

$$\Gamma\text{f}_j = \text{Fc}_j \text{ sign}\,(\,\dot{q}_j) + \text{Fv}_j\;\; \dot{q}_j + \text{Off}_j \qquad (4)$$

In addition to inertial parameters, there are 14 friction parameters (coefficients of viscous friction Fvj and Coulomb friction Fcj for each joint) and 7 offset parameters Offj that take into account the offset of the joint torque and the asymmetry of Coulomb friction. (4) represents the simplified model of dry and viscous friction in joint j used for nonzero velocities. In total, there are 71 dynamic parameters to identify.

3 Identification method

3.1 IDIM_LS method

Applied successfully on several industrial robots and prototypes, IDIM_LS is the most common method for identifying robot parameters. It makes possible estimating the parameters using the inverse dynamic model and least square, knowing the torque and the articular positions. Fig. 2 shows the principle of the IDIM_LS identification method [7]. Due to model errors and measurement noises, the real motor torques **Γ** are different from the model torques $\boldsymbol{\Gamma}_{\textbf{mdi}}$ (5).

$$\Gamma = \text{LIDM}\big(q, \hat{\dot{q}},\, \hat{\ddot{q}}\big)\chi + \varepsilon \qquad (5)$$

With ε is errors and measurement noises.
The first and second derivatives of the positions $\hat{\dot{q}}$, $\hat{\ddot{q}}$ are estimated using a centred derivative filter. This filter is applied after deleting the absurd samples via a median filter of order 5.
After sampling (5) and regrouping the samples for all the axes, we obtain overdetermined system (6). (7) represents an ordinary solution for this system, utilizing the least square method by minimizing ρ.

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

$$\hat{\chi} = (W^T W)^{-1} W^T . Y = W^+ Y \qquad (7)$$

Where:
- Y is the vector of sampled Γ measurements.
- W is the observation matrix constructed by LIDM sampling.
- ρ is the residue vector.

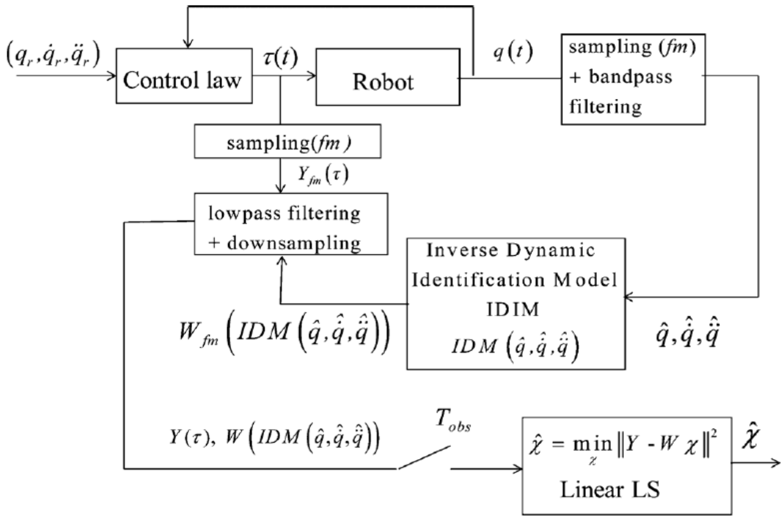

Fig. 2 Principle of IDIM_LS identification method [7].

3.2 Optimization

We have noticed that the identified vector $\hat{\chi}$ using the least squares method has unrealistic values, that do not correspond to the physical sense of the parameter. For this reason, a numerical optimization was done.
This optimization is based on estimating parameters by minimizing different criteria. The first criterion is the quadratic error between the measured and estimated torques. The implementation of numerical optimization is done with "fminsearch" function of the MATLAB software.

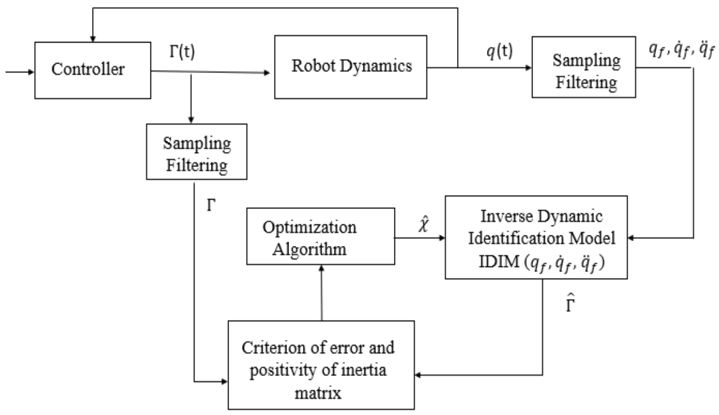

Fig. 3 Identification method with parameter optimization algorithm.

Fig. 3 shows the principle of the identification method with the optimization of the parameters. The inertia matrix of the robot must be strictly positive. Therefore, this second criterion was added to the optimisation program.

The decomposition of the eigenvalues of the inertia matrix allow us to check its positive definiteness, either with Sylvester's theorem or with a Cholesky decomposition. According to [16], Sylvester's theorem allows to find conditions that the parameters must check to obtain the positive definiteness. The Cholesky decomposition has the advantage that a tolerance is defined and takes into account the noise and the measurement error [3].
We opted for two steps: In the first step, we checked the positivity of the eigenvalues of the inertia matrix throughout the identification trajectory. In the second step, using the optimal estimated parameters derived from the first step, we verified the criterions in all the workspace by changing the robot trajectory.

3.3 Precision of estimated parameters

During the optimization iterations, poorly identified parameters that do not affect the calculation of estimated torques were eliminated. This allowed us to reduce the number of basic parameters from 71 to 57. Those essential basic parameters simplify the dynamic model of the robot and minimize the error between this model and the robot's real dynamic model.
Using classical method with statistical properties, we calculate the precision of the identified parameters. The calculation method was detailed in work done by [17].
We admit that the robot model based on the estimated parameters has the same behaviour as the real robot. The error e between the vector of estimated parameters $\hat{\chi}$ and the optimal value χ^* is calculated by (8).

$$e = \hat{\chi} - \chi^* \tag{8}$$

$$\sigma^2 = CRT/(n-d) \tag{9}$$

where n is the number of measurement samples, d the number of estimated parameters, σ^2 is the noise variance and CRT is a criterion applied for the calculation of the precision defined by [17].

$$\%P_{\hat{\chi}} = 100 \times \sqrt{\operatorname{diag} \sigma^2}/\hat{\chi} \tag{10}$$

The accuracy of the identified parameters is calculated with (10). $P_{\hat{\chi}}$ is an indicator of the uncertainty of estimated parameters.

4 Experimentation and results

4.1 Data measurement and filtering

The articular positions q and the torque references Γ are acquired at the frequency of 250 Hz while the robot follows an exciting trajectory. We performed the measurements using a robot simulator (RobotStudio) and a measurement software (Test Signal Viewer). This trajectory (Fig. 4) was defined in order to ensure a good conditioning of the observation matrix W. To calculate the matrix observations W, the articular velocities and accelerations are estimated using a limited bandwidth derivative filter. This filter is applied after deleting the aberrant samples via a median filter of order 5. Fig.4 shows the exciting articular trajectories of each axis and its corresponding velocities. Due to the fact that some robot articulations have the same position and speed throughout the whole chosen trajectory. The figure shows overlapping position and speed graphs for the 7 Yumi robot joints.
The overdetermined system (6) is obtained after parallel filtering of the experimentally measured torques Y and of each noisy column of the matrix W. We used for that 5th-order lowpass Butterworth filter round-trip with a cut-off frequency of 10 Hz. The estimated parameters $\hat{\chi}$ are the linear least squares solution of this overdetermined system. They were estimated using the basic parameters defined by [18], and calculated automatically using the SYMORO + software.

4.2 Results

Before presenting the results obtained, we would like to clarify why we have chosen the optimization method. We used the classical method to identify dynamic parameters. It is impossible to have dynamic robotic system with negative inertia matrix or negative motor inertia. However, the results we found showed that it was the case for some identified parameters. Therefore, a different method is needed.

After applying the identification method with parameter optimization algorithm explained in section 3.2 (Fig. 3) to a single arm of the YuMi robot. We were able to identify 57 parameters with sufficient accuracy. The estimated friction and offsets parameters for the axes 1, 2, 3 and 4 were identified with a good accuracy, varying from 0.3% to 1.9%. However, for the axes 5, 6 and 7 (4, 5 and 6 according to robot manual numbering) the inaccuracy is bigger but still acceptable and varies between 2% to 7% (Table 2). From the results shown in (Fig. 5, 6) the same remark can be made for the torques. The NRMSE (Normalized Root-Mean-Square Error) values between measured and estimated torques are 3.65%, 1.37%, 9.24% and 3.77% for the 1, 2, 3 and 4 axes, and 16.38%, 16.86% and 13.02% for 5,6 and 7 axes respectively (according to our chosen order of axes numbering).

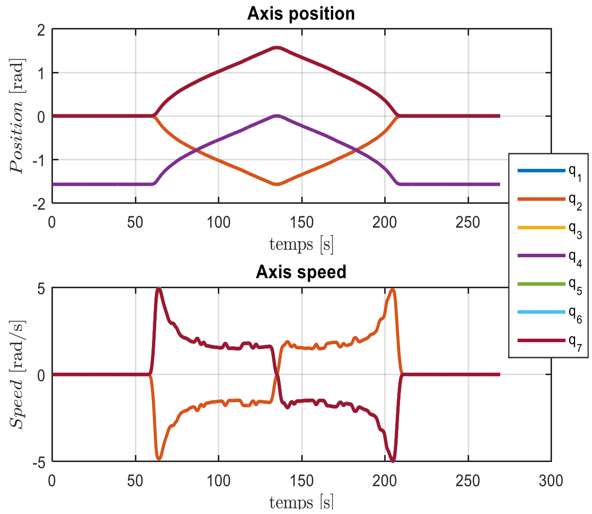

Fig. 4 Exciting trajectories and speeds used for the 7 joints identification.

Table2. Results of identification of friction parameters and offsets

Parameter	$\widehat{\chi}_{optim}$	$\%P_{\widehat{\chi}}$
Off_1	3.117	8.05
Off_2	1.241	5.82
Off_4	-0.447	7.26
Off_5	0.08	11.88
Off_6	-0.17	3.40
Off_7	-0.011	15.93
Fc_1	2.175	**0.38**
Fv_1	0.367	**0.99**
Fc_2	1.826	**0.52**
Fv_2	0.758	**0.61**
Fc_3	0.718	**1.05**
Fv_3	0.183	**1.97**
Fc_4	0.836	**0.89**
Fv_4	0.18	**1.90**
Fc_5	0.228	2.87
Fv_5	0.044	6.65
Fc_6	0.183	3.58
Fv_6	0.039	7.52
Fc_7	0.132	4.93
Fv_7	0.045	6.43

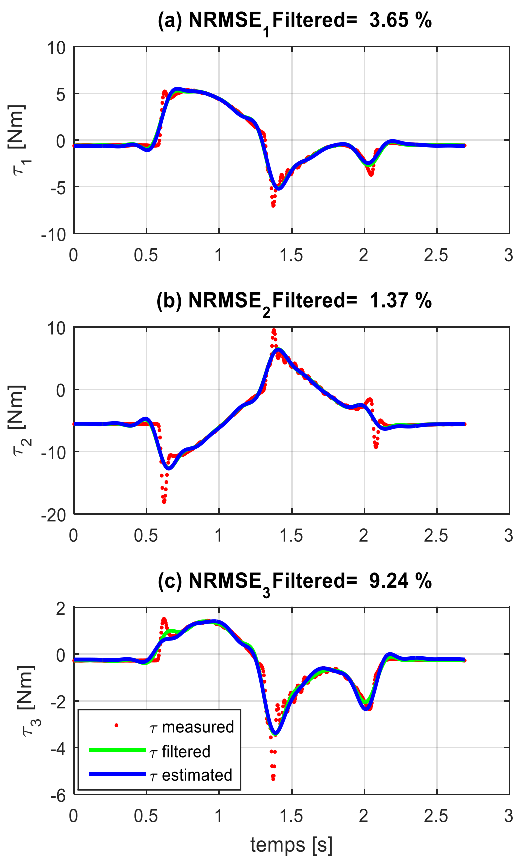

Fig. 5 Comparison of measured, filtered and estimated torques for joints 1 (a), 2 (b) and 3 (c)

Note that $(XX, \ldots.)$, $(MX \ldots)$, Fv, Fc and Off are expressed respectively in $\mathrm{kg}.m^2$, kg. m, N. m. s, N. m and N. m.

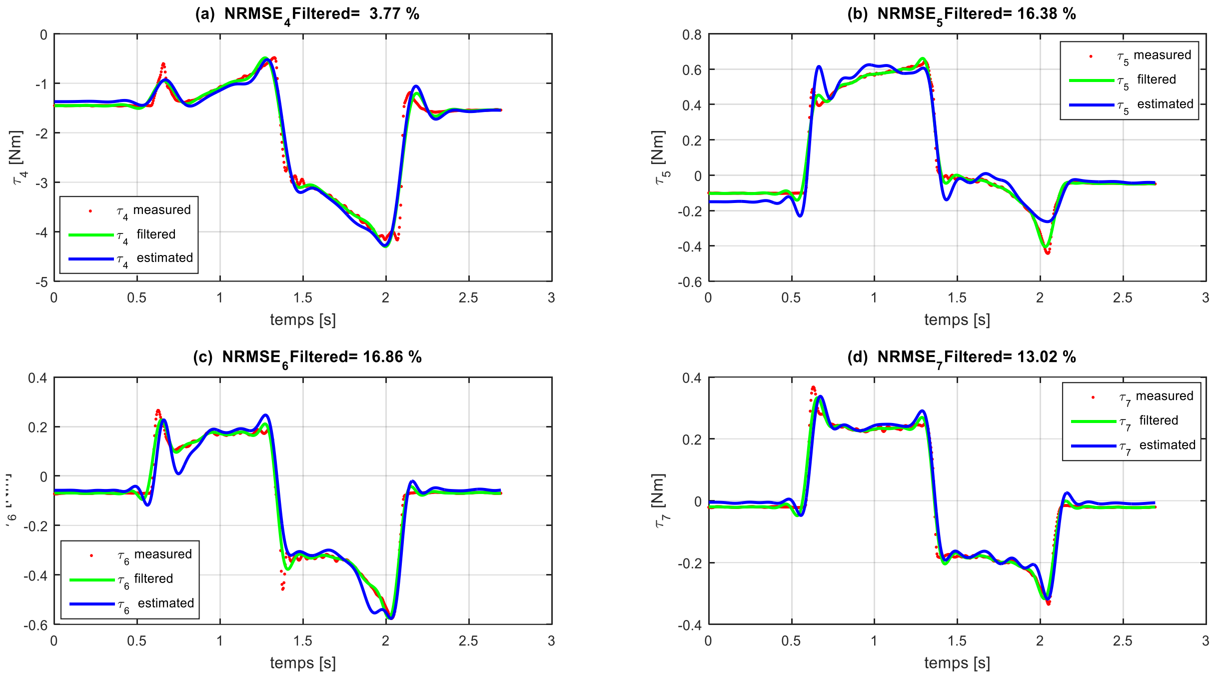

Fig. 6 Comparison of measured, filtered and estimated torques for joints 4 (a), 5 (b), 6 (c) and 7 (

Table 3. Identified Inertial parameters

Param	$\hat{\chi}$	$\%P_{\hat{\chi}}$	Param	$\hat{\chi}$	$\%P_{\hat{\chi}}$
ZZ_{R1}	0.064	14.58	MY_{R4}	0.244	1.71
MX_{R1}	0.093	8.35	XX_{R5}	-0.023	10.44
MY_{R1}	0.391	7.58	XY_{R5}	-0.038	2.93
XX_{R2}	0.214	8.94	XZ_{R5}	0.01	4.43
XZ_{R2}	0.101	2.57	ZZ_{R5}	-0.0047	6.94
ZZ_{R2}	0.224	6.30	MX_{R5}	0.0304	2.43
MX_{R2}	0.267	4.09	MY_{R5}	0.0135	8.00
MY_{R2}	-0.784	0.68	XY_{R6}	0.0078	7.12
XX_{R3}	-0.105	10.55	XZ_{R6}	-0.0017	13.94
XY_{R3}	-0.112	6.45	ZZ_{R6}	0.0033	10.20
XZ_{R3}	-0.027	12.65	MX_{R6}	0.0041	15.18
YZ_{R3}	0.139	5.07	MY_{R6}	-0.0166	6.69
ZZ_{R3}	0.054	11.55	YZ_7	-0.0013	12.04
MX_{R3}	0.106	3.88	ZZ_7	0.0007	6.87
MY_{R3}	0.025	8.03	MY_7	0.0033	7.35
XX_{R4}	-0.033	14.70	Ia_3	0.0319	18.65
XY_{R4}	0.026	4.53	Ia_4	0.0663	2.80
XZ_{R4}	0.009	16.92	Ia_5	0.0119	7.17
MX_{R4}	0.054	7.01			

Table 3 presents the estimated numerical values of the dynamic inertial parameters. In general, the accuracy is acceptable and varies between 0.68% and 18%. High inaccuracies are observed in inertial parameters that have small numerical values (for example XXR4 and MXR6). The identification of those parameters can be improved with more optimization iterations.

The inaccuracy of the last 3 joints is influenced by the used simple friction model (4) and can be improved by developing a more complex friction model for the YuMi robot.

Moreover, during experiments, those axes were more sensitive to noises during acceleration phase. This can be linked to the PID cascaded control structure used for each joint of the robot [19].

Conclusion

This article presents the dynamic identification of the parameters of the ABB IRB14000 collaborative industrial robot. The identification was done using the inverse dynamic model and least squares method. We subsequently found that the vector identified using the least squares method has unrealistic values, which do not correspond to the physical significance of the parameter. For this reason, a numerical optimization was carried out. We optimized the estimated vector of the parameters with numerical optimization in MATLAB, to have practical values consistent with their physical meaning. Numerical values were presented to help researchers interested in developing and improving the results of this study. In the perspective of this work, it is proposed to replace the friction model used by a more complex and precise model or to use more exciting trajectories than those used in our study.

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