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NONLINEAR GREY-BOX IDENTIFICATION OF INDUSTRIAL ROBOTS CONTAINING FLEXIBILITIES [1]

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Abstract: Nonlinear grey-box identification of industrial robots is considered. A three-step identification procedure is proposed in which parameters for rigid body dynamics, friction, and flexibilities can be identified only using measurements on the motor. In the first two steps, good initial parameter estimates are derived which are used in the last step, where the parameters of a nonlinear physically parameterized model are identified directly in the time domain. The procedure is exemplified using real data from an experimental industrial robot. *Copyright © 2005 IFAC.*

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1. INTRODUCTION

System identification in robotics is a vast research area and can be divided into, at least, three different levels or application areas. These levels involve the estimation of the kinematic description, the dynamic model (often divided into rigid body and flexible body dynamics), and the joint model (*e.g.*, motor inertia, gearbox elasticity and backlash, motor characteristics, and friction parameters). Some results on the latter two areas are mentioned in Section 4. An overview of identification in robotics can also be found in (Kozlowski, 1998).

Nominal parameter values can, for the kinematics and rigid body dynamics, often be obtained from CAD models. Most of the joint model parameters are often measured in a test bench. Flexibilities and friction parameters are harder to find and therefore tuned after assembly. However, to obtain high accuracy, all parameters must usually be tuned by the use of experimental data. The development rate of new industrial robots is also high, with several kinds of robots and different configurations to tune each year. For top performance, there could also be a need to re-tune robots at the customer site due to wear or other changing conditions. This means that there is an increasing need for good identification procedures.

In the work presented here, a three-step identification procedure is proposed in which parameters for rigid body dynamics, friction, and flexibilities can be identified only using measurements on the motor side of the flexibility. The main point is the last step, where the parameters of a nonlinear physically parameterized model (a nonlinear grey-box model) are identified directly in the time domain. The first two steps give special attention to the problem of finding good initial parameter estimates for the iterative optimization routine. The procedure is exemplified using real data from an experimental industrial robot.

The work reported here is closely related to the problems considered in, for example, (Östring *et al.*, 2003; Isaksson *et al.*, 2003). In (Östring *et al.*, 2003), a method is applied where inertial parameters as well as parameters describing the flexibility can be identified directly in the time domain. This is done by utilizing a user-defined model structure in the System Identification Toolbox (SITB). However, only linear models were considered in their work. (Isaksson *et al.*, 2003)

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consider grey-box identification of a two-mass model with backlash, where black-box modeling is used to find initial parameter values.

The paper is organized as follows. In Section 2 the nonlinear grey-box identification problem is briefly described and Section 3 shows the nonlinear robot model used for identification. The three-step identification procedure is presented in Section 4. In Section 5 the data collection is described, and Section 6 shows the results from applying the proposed identification procedure to the experimental data. Finally, Section 7 contains some conclusions and notes on future work.

2. NONLINEAR GREY-BOX IDENTIFICATION

The starting point for the nonlinear grey-box identification is the continuous time state space model structure

$$\dot{x}(t) = f(t, x(t), \theta, u(t)) \quad (1a)$$
$$y(t) = h(t, x(t), \theta, u(t)) + e(t) \quad (1b)$$

where f and h are nonlinear functions. $x(t)$ is the state vector, $u(t)$ and $y(t)$ are input and output signals, $e(t)$ a white measurement disturbance signal, and t denotes time. Finally θ is the vector of unknown parameters. Given a set of input/output-data the aim is to determine the parameter vector that minimizes a criterion like

$$V_N(\theta) = \frac{1}{N}\sum_{t=1}^{N} \varepsilon^2(t, \theta) \quad (2)$$

where $\varepsilon(t)$ denotes the prediction error

$$\varepsilon(t, \theta) = y(t) - \hat{y}(t, \theta) \quad (3)$$

The experiments presented in this paper will utilize the nonlinear grey-box model structure NLGREY, available in a beta version of a nonlinear extension to the System Identification Toolbox (SITB), (Ljung, 2003). The model structure NLGREY is similar to the IDGREY model structure in SITB. The model can be either a discrete or continuous time state space model, and it is defined in a Matlab m-file/mex-file. In the current version of the software, only OE-models can be used, *i.e.* only additive white noise, $e(t)$, on the output. The prediction $\hat{y}(t|\theta)$ then becomes the simulated output of the model (1) with the input $u(t)$ (without $e(t)$) for the current parameter vector θ. The data set, $\{y, u\}$, is put into an IDDATA object and θ is estimated by applying a prediction error method, which performs a numerical optimization of the criterion (2) by an iterative numerical search algorithm. This search algorithm involves simulation of the system for different values of θ. The user specifies an initial parameter vector and it is also possible to fix some components in θ. To speed up the numerical optimization, the simulation model is implemented in a mex-file (C-code).

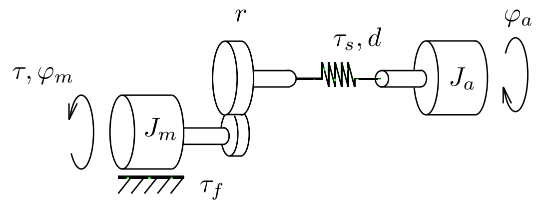

Fig. 1. The two-mass flexible model of the robot arm.

3. ROBOT MODEL

The industrial robot that will be studied in this paper is, for movements around an axis not affected by gravity, modeled by a nonlinear two-mass flexible model which is illustrated in Figure 1. A two-mass model is probably too simple to describe the true system (see, for example, (Östring *et al.*, 2003) or Figure 3), but it can still be used as an illustration of the proposed identification procedure.

The differential equations describing the dynamics of the robot arm are

$$J_m\ddot{\varphi}_m + rd(r\dot{\varphi}_m - \dot{\varphi}_a) + \tau_f + r\tau_s = \tau \quad (4)$$
$$J_a\ddot{\varphi}_a - d(r\dot{\varphi}_m - \dot{\varphi}_a) - \tau_s = 0 \quad (5)$$

where J_m and J_a are the moments of inertia of the motor and arm respectively, r is the gear ratio, τ is the motor torque and d is the damping parameter. The spring and gear friction torques, τ_s and τ_f respectively, are often approximately modeled by linear models (see, for example, (Östring *et al.*, 2003)). In this work, nonlinear models will be used to capture the effect of the Coulomb friction and to get a more realistic model of the spring. The torque of the spring is modeled as

$$\tau_s = k_1(r\varphi_m - \varphi_a) + k_3(r\varphi_m - \varphi_a)^3 \quad (6)$$

where φ_m and φ_a are the angles of the motor and arm respectively, and k_1 and k_3 are the parameters of the spring. The torque due to friction is modeled as

$$\tau_f = F_v\dot{\varphi}_m + F_c\,\mathrm{sgn}(\dot{\varphi}_m) \quad (7)$$

where F_v and F_c are the viscous and Coulomb friction coefficients. A third nonlinearity of practical importance is the presence of backlash in the gearbox, but this problem is left for future work. See also (Isaksson *et al.*, 2003). Using (4) to (7), a nonlinear state space model of the system can be derived. The motor torque, τ, is used as input, u, and with the states defined as

$$x = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} r\varphi_m - \varphi_a \\ \dot{\varphi}_m \\ \dot{\varphi}_a \end{pmatrix} \quad (8)$$

the state space equations become

$$\dot{x}_1 = rx_2 - x_3 \quad (9a)$$
$$\dot{x}_2 = \frac{1}{J_m}\Big(- F_v x_2 - F_c\,\mathrm{sgn}(x_2) - rd(rx_2 - x_3) - rk_1x_1 - rk_3x_1^3 + u\Big) \quad (9b)$$
$$\dot{x}_3 = \frac{1}{J_a}\Big(d(rx_2 - x_3) + k_1x_1 + k_3x_1^3\Big) \quad (9c)$$