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State Space Estimation Method for Robot Identification

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Abstract: In this paper, we study the identification of robot dynamic models. The usual technique, based on the Least-Squares method, is carefully detailed. A new procedure based on Kalman filtering and fixed interval smoothing is developed. This new technique is compared to usual one with simulated and experimental data. The obtained results show that the proposed technique is a credible alternative, especially if the system bandwidth is unknown.

Keywords: Robots identification; System identification; Closed-loop identification; Least-squares identification; Parameter identification; Kalman filters; State observers

1. INTRODUCTION

The usual method for robot identification is based on the Least-Squares (LS) technique and the Inverse Dynamic Identification Model (IDIM). The IDIM indeed allows expressing the input torque as a linear function of the physical parameters thanks to the modified Denavit and Hartenberg (DHM) notation. Therefore, the IDIM-LS method is a really practical solution, which explains its success, see (Gautier, Janot & Vandanjon 2013) and the references given therein. However this method needs a well-tuned band pass filtering to get the derivatives of the joint positions. It requires a good a priori knowledge of the system to tune adequately the filters. That may be an issue for the early tests of a system, especially if there is no access to the key design parameters, such as a robot bought "off-the-shelf".

The goal of this article is twofold: first, to make clear the usual process of robot identification for people not related to this field; second, to show how this process can be improved. Robot identification may indeed be difficult for people coming from the general field of system identification, since the techniques rely on a priori knowledge of the system. For this work, the author designates by "a priori knowledge" the values of the parameters, which are known or guessed prior to the identification. In any case, the model structure is assumed to be known.

As it will be seen, the main part of the work consists in differentiating the position signal to construct the regressors (see Section 3 for a proper definition) for the LS method. In many fields, the problem of differentiating numerical signals was raised. In the domain of continuous-time system identification, it has been successfully dealt by different techniques like the generalized Poisson moment functional (GPMF) in (Rao & Unbehauen 2006), the State Variable Filters (SVF) in (Mahata & Garnier 2006) or the Refined Instrumental Variable (RIV) in (Garnier et al. 2007). For further reading on the topic, see e.g. (Garnier, Mensler & Richard 2003). Nevertheless, those attractive methods require either the system to be linear in the states, in order to have a self-tuned filtering (RIV), or the user to provide the bandwidth for the filter (GPMF and SVF). As it will be seen, for a robot, the regressors are non-linear in the states. Hence, those techniques do not fulfil the requirements of our study. It would be worth to look at other fields to find a technique which does not require a priori knowledge of the system and which can handle non-linearities in the states.

The plan of this article is as follows. Firstly, the tools and methods considered are presented. Secondly, the results in simulation of numerical differentiation and parameters identification are summarized. Afterwards, the techniques are compared with experimental data. Then, two cases are considered: first, high precision position sensor is used; second, the precision is deteriorated. Finally, concluding remarks are expressed.

2. CLOSED-LOOP SYSTEM IDENTIFICATION

Traditionally, the closed-loop identification methods are divided in three main categories, see e.g. (Forssell & Ljung 1999). The first one, called direct approach, consists in identifying the open-loop system without taking into account the feedback loop. As it will be seen, it requires a careful process of the data to avoid biased estimation. The second category is the indirect approach. In this case, the knowledge of controller, or at least of the reference signal, is required to

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identify the closed-loop system. The last category is the joint input-output approach, which consists in using open-loop techniques by considering at the same time the input and the output as an augmented output of the whole closed-loop system.

As it will be presented in the next section, robot identification usually relies on IDIM-LS and belongs to the direct approach. Recently, the Instrumental Variable method has proven to be interesting improvement, see e.g. (Janot, Vandanjon & Gautier 2014) or (Brunot et al. 2015). This last method identifies the open-loop system but it relies on the simulation of the whole closed-loop system. This article focuses on direct approach methods in order to deal with robots whose the controller may be unknown.

3. LEAST-SQUARES for ROBOT IDENTIFICATION

3.1 Inverse Dynamic Model

If a robot with n moving links is considered, the $(n\times 1)$ vector $\boldsymbol{\tau}(t)$ contains the inputs of those links, which are the applied forces or torques. The signals $\mathbf{q}(t)$, $\dot{\mathbf{q}}(t)$ and $\ddot{\mathbf{q}}(t)$ are respectively the $(n\times 1)$ vectors of generalized joint positions, velocities and accelerations. With respect to the Newton's second law it comes out:

$$\mathbf{M}(\mathbf{q}(\mathrm{t}))\ddot{\mathbf{q}}(\mathrm{t}) = \boldsymbol{\tau}(\mathrm{t}) - \mathbf{N}(\mathbf{q}(\mathrm{t}),\dot{\mathbf{q}}(\mathrm{t})) \tag{1}$$

where, $\mathbf{M}(\mathbf{q}(\mathrm{t}))$ is the $(n\times n)$ inertia matrix of the robot, and $\mathbf{N}(\mathbf{q}(\mathrm{t}),\dot{\mathbf{q}}(\mathrm{t}))$ is the $(n\times 1)$ vector modelling the disturbances or perturbations. Those perturbations contain the friction forces, gravity effects and other non-linearities depending on the studied robot. Experience has shown that those disturbances are, in the vast majority of cases, linear in the parameters, but not in the states. Therefore, it appears to be very convenient for the identification to consider the Inverse Dynamic Model (IDM). The IDM is described by (2), where: the input is the dependent (or observation) variable; $\boldsymbol{\varphi}$ is the $(n\times n_\theta)$ matrix of regressors (or independent variables); $\boldsymbol{\theta}$ is the $(n_\theta\times 1)$ vector of dynamic parameters to be estimated.

$$\boldsymbol{\tau}(t) = \boldsymbol{\varphi}(\mathbf{q}(\mathrm{t}),\dot{\mathbf{q}}(\mathrm{t}),\ddot{\mathbf{q}}(\mathrm{t}))\boldsymbol{\theta} \tag{2}$$

3.2 Least-Squares Equation

The model described by (2) can straightforwardly be extended to the vector-matrix form:

$$\mathbf{u}_m = \begin{bmatrix} \boldsymbol{\tau}(t_1) \\ \vdots \\ \boldsymbol{\tau}(N_s) \end{bmatrix} = \mathbf{X}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}})\boldsymbol{\theta} + \mathbf{e}_{LS} \tag{3}$$

where, $\mathbf{u}_m$ is a $(N_t\times 1)$ vector constructed with the measured signals, $\mathbf{X}$ is a $(N_t\times n_\theta)$ matrix whose each column is called a regressor and $\mathbf{e}_{LS}$ is a $(N_t\times 1)$ vector of error terms, with $N_t = N_s n$ and N_s the number of sampled points considered. It is assumed that $\mathbf{X}$ is full rank, i.e. $rank(\mathbf{X}) = n_\theta$, and that $N_t \gg n_\theta$, to have an over-determined system of equations.

From (3), the Least-Squares (LS) estimates and their associated covariance matrix are given by:

$$\hat{\boldsymbol{\theta}}_{LS} = \left(\mathbf{X}^T\mathbf{X}\right)^{-1}\mathbf{X}^T\mathbf{u}_m \tag{4}$$

$$\boldsymbol{\Sigma}_{LS} = \sigma^2\left(\mathbf{X}^T\mathbf{X}\right)^{-1} \tag{5}$$

$$\hat{\sigma}^2 = \frac{1}{N_t - n_\theta}\left\|\mathbf{u}_m - \mathbf{X}\hat{\boldsymbol{\theta}}_{LS}\right\|^2 \tag{6}$$

From a theoretical point of view, the LS estimates (4) are unbiased if the error has a zero mean and if the regressors are uncorrelated with the error, see relations (7).

$$E[\mathbf{e}_{LS}] = 0 \qquad E\left[\mathbf{X}^T\mathbf{e}_{LS}\right] = E\left[\mathbf{X}^T\right]E[\mathbf{e}_{LS}] = 0 \tag{7}$$

The covariance matrix given by (5) assumes that $\mathbf{X}$ is deterministic and that $\mathbf{e}_{LS}$ is homoscedastic i.e. $\mathrm{var}(\mathbf{e}_{LS}(t)) = \sigma^2$, for each t. It is assumed that those two assumptions hold. However, systems considered in this article operate in closed-loop. In that case, the assumption given by (7) does not hold (Van den Hof 1998). This partly explains why a tailor-made pre-filtering of the data is done in practice.

3.3 States Estimation by Tailor-Made Filtering

To build the regressors matrix $\mathbf{X}$, the velocity and the acceleration are estimated from the measured position. As described in (Gautier 1997), the classical technique used in robots identification is divided in three sequential steps. Those steps are influenced by the sampling frequency, noted ω_s. This frequency is usually chosen 100 times larger than the natural frequency of the highest mode which must be modelled, $\omega_{dyn} = \omega_s/100$, in order to satisfy the Nyquist rule.

Step 1. The first step consists in reconstructing the missing data, or, more practically, to compute the derivatives of the measured position. It is usually done thanks to numerical differentiation (centred scheme). Prior to this, to avoid amplification of the noise at high frequency, a low-pass filtering is undertaken. This filter is applied forward and backward to avoid phase lag introduction. It is a Butterworth filter, whose order is $n_d + 2$. Where n_d is the desired derivative order, which is usually equal to two. The issue is to choose the cutting frequency of the filter, ω_q, to have $\hat{\dot{q}}(t) = \dot{q}(t)$ and $\hat{\ddot{q}}(t) = \ddot{q}(t)$ over the frequency range of the system. The rule of thumb is to take it as $2\omega_{dyn} \le \omega_q \le 10\omega_{dyn}$. It obviously requires knowledge about the system.

Step2. A filter is then applied to all signals. The objective is to remove high frequencies perturbations in the dependent variable measurements (generally, the input torque). To be