State Space Estimation Method for the Identification of an Industrial Robot Arm

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Abstract: In this paper, we study the identification of industrial robot dynamic models. Since the models are linear with respect to the parameters, the usual identification technique is based on the Least-Squares method. That requires a careful preprocessing of the data to obtain consistent estimates of the dynamic parameters. The preprocessing mainly consists in estimating the joint velocities and accelerations from the measured joint positions. In this paper, we carefully detail this process and propose a new procedure based on Kalman filtering and fixed interval smoothing. This new technique is compared to usual one with experimental data considering an industrial robot arm. The obtained results show that the proposed technique is a credible alternative, especially if the system bandwidth is unknown.

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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 practical solution, which explains its success, see (Gautier et al., 2013) and the references given therein. However this method needs a well-tunned band pass filter to get the derivatives of the joint positions. Thus, 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, as with a robot bought "off-the-shelf".

This article has two aims. Firstly, it develops the usual process of robot identification. Secondly, the new technique proposed in (Brunot et al., 2016) is tested on an industrial robot arm. This technique has already proven to be a suitable solution for a prototype robot with one degree of freedom. Its principle is to avoid relying on a priori knowledge of the system. For this work, the authors designate 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 measured joint position signals to estimate the joint velocities and accelerations required 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 and Unbehauen, 2006), the State Variable Filters (SVF) in (Mahata and Garnier, 2006) or the Refined Instrumental Variable (RIV) in (Garnier et al., 2007). For further reading on the topic, see e.g. (Garnier et al., 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 fulfill the requirements of our study. Therefore, 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 usual method for robot identification is presented. Secondly, the new solution based on a Kalman filter and a fixed interval smoother is introduced. Afterwards, the techniques are compared with experimental data from a Stäubli TX40 industrial robot arm. Two cases are considered: first, a good a priori knowledge on the system which allows a good bandpass filtering; second, an inadequate bandpass filtering due to a lack of knowledge concerning the robot. Finally, concluding remarks are expressed.

2. LEAST-SQUARES FOR ROBOT IDENTIFICATION

2.1 Inverse Dynamic Identification Model

If a robot with \( n \) moving links is considered, the vector \( \tau(t) \) contains the inputs of those links, which are the applied forces or torques. The signals \( q(t) \), \( \dot{q}(t) \) and \( \ddot{q}(t) \) 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:
\[ M(q(t)) \ddot{q}(t) = \tau(t) - N(q(t), \dot{q}(t)) \] (1)

where, \( M(q(t)) \) is the \((n \times n)\) inertia matrix of the robot, and \( N(q(t), \dot{q}(t)) \) 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 torque is the dependent (or observation) variable; \( \phi \) is the \((n \times b)\) matrix of regressors (or independent variables); \( \theta \) is the \((b \times 1)\) vector of base parameters to estimate.

\[ \tau_{idm}(t) = \phi(q(t), \dot{q}(t), \ddot{q}(t)) \theta \] (2)

Because of perturbations coming from measurement noise and modelling errors, the actual torque \( \tau \) differs from \( \tau_{idm} \) by an error \( v \). The Inverse Dynamic Identification Model (IDM) is given by

\[ \tau(t) = \tau_{idm}(t) + v(t) = \phi(q(t), \dot{q}(t), \ddot{q}(t)) \theta + v(t). \] (3)

### 2.2 Least-Squares Equation

The model described by (3) can straightforwardly be extended to the vector-matrix form:

\[ u_m = \begin{bmatrix} \tau(t_1) \\ \vdots \\ \tau(t_{N_t}) \end{bmatrix} = X(q, \dot{q}, \ddot{q}) \theta + e_{LS}. \] (4)

where, \( u_m \) is a \((N_t \times 1)\) vector constructed with the measured signals, \( X \) is a \((N_t \times b)\) matrix composed of the regressors and \( e_{LS} \) is a \((N_t \times 1)\) vector of error terms, with \( N_t = n_N s \) and \( N_s \) the number of sampled points considered. It is assumed that \( X \) is full rank, i.e. \( \text{rank}(X) = b \), and that \( N_t \gg b \), to have an over-determined system of equations. From (4), the Least-Squares (LS) estimates and their associated covariance matrix are given by (see e.g. (Gautier et al., 2013)):

\[ \hat{\theta}_{LS} = (X^T X)^{-1} X^T u_m \] (5)

\[ \Sigma_{LS} = \sigma^2 (X^T X)^{-1} \] (6)

\[ \sigma^2 = \frac{1}{N_t - b} \| u_m - X \hat{\theta}_{LS} \|^2. \] (7)

From a theoretical point of view, the LS estimates (5) are unbiased if the error has a zero mean and if the regressors are uncorrelated with the error, see relations (8).

\[ E[e_{LS}] = 0, \quad E[X^T e_{LS}] = 0 \] (8)

The covariance matrix given by Eq. (6) assumes that \( X \) is deterministic and that \( e_{LS} \) is homoscedastic i.e. \( \text{var}(e_{LS}(t)) = \sigma^2 \), for each \( t \). It is assumed that those two assumptions hold. However, systems considered in this article operate in closed-loop, since they are unstable in open-loop. In that case, the assumption given by (8) does not hold (Van den Hof, 1998). This partly explains why a tailor-made pre-filtering of the data is done in practice.

### 2.3 States Estimation by Tailor-Made Filtering

This part emphasizes the classical technique used in robots identification to construct the regressors matrix \( X \). Since the regressors vectors are function of the states, the work mainly consists in estimating the velocity and the acceleration from the measured position. As described in (Gautier, 1997) or more recently in (Gautier et al., 2013), the data pre-processing is divided in four sequential steps. Those steps are influenced by the sampling frequency, noted \( \omega_s \). This frequency is usually chosen 100 times larger than the natural frequency of the highest mode, \( \omega_{dy n} = \omega_s/100 \), which must be modelled, 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, \( \omega_p \), to have \( \hat{\omega}(t) = \hat{q}(t) \) and \( \hat{\dot{\omega}}(t) = \hat{\ddot{q}}(t) \) over the frequency range of the system. The rule of thumb is to take it as \( 2\omega_{dy n} \leq \omega_p \leq 10\omega_{dy n} \). It obviously requires knowledge about the system.

**Step 2.** The observation matrix is constructed with the estimated signals from the previous step: \( X(\hat{q}, \dot{q}, \ddot{q}) \).

**Step 3.** 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 consistent, this filter is also applied to the independent variables. Its cut-off frequency, \( \omega_f \), is chosen at about \( \omega_f \geq 2\omega_{dy n} \).

**Step 4.** After the previous step, the signals do not contain any information above \( \omega_f \). Therefore, they are re-sampled at a lower frequency (down-sampling). This frequency is usually taken equal to \( \omega_f \).

In practice, three elements are worth noting. First, the filters frequencies may be defined taking into account the excitation signal spectrum instead of \( \omega_{dy n} \). The second element is that, with MatLab\textsuperscript{®}, the two last steps are performed simultaneously with the decimate function. The last element is that the described methodology is a rule of thumb. It only provides approximate relations or intervals. The choice relies on the practitioner skills. This is why another way is investigated for users without solid background in robotic identification in order to perform the step 1. The decimate filter is still considered for steps 3 and 4 to have a fair comparison with the classical technique by taking into account the same number of data points.

### 3. Kalman Filter and Integrated Random Walk

#### 3.1 The State Space Model: IRW

Many methods have been developed to deal with the numerical differentiation issue; see e.g. (Drídi et al., 2010). Nonetheless, the goal is here to suggest a practical and straightforward technique. Therefore, the study will focus on the well-known Kalman filter technique, in a discrete time framework. This technique is summarized in (Norton, 1975) or (Young, 2000). It allows an off-line estimation of the states without using the dynamic model, unlike High Gain observers for instance. Equation (9) defines the state
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