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A virtual force sensor for interaction tasks with conventional industrial robots☆

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ABSTRACT

The attempt to use industrial robots for technological and interaction tasks, *i.e.,* robotic machining and robotic assembling, implies on the one hand the knowledge of the interaction force, on the other hand the reduction of physical sensors. The aim of this work is the development of a virtual force sensor to estimate the interaction force between a conventional industrial robot and the environment. The goal is achieved by exploiting a task oriented dynamics model calibration combined with of a thermal friction model of the robot. The dynamics model is calibrated by means of exciting trajectories made by suitable paths selected by a genetic-based two-stage optimization. The virtual sensor is proven by means of a polishing application. The proposed approach is successfully compared with state-of-the-art approaches. Finally, the use of the virtual force sensor in a closed-loop architecture highlights the effectiveness of the method in real applications.

1. Introduction

The adoption of industrial robots in tasks where material removal and mechanical assembly are required is still challenging despite more than 30 years of investigations.

It is well known that model-based control strategies [1], based on robot dynamics model calibration, can improve the dynamics performance of the manipulator used in interaction tasks. During the execution of such tasks, it is often required to measure and control the interaction force between the manipulator and the environment [2].

Robot dynamics modelling and calibration techniques were widely addressed along the last three decades. Since early works [3,4] many researchers have investigated methodologies all involving a linear reduction of the rigid-body model into a *base* set of lumped dynamics model parameters (BP) to be estimated [5,6].

The accuracy in torque prediction relies on the conditioning properties of the resulting kinematic function (regressor) that maps the manipulator model parameters into torques. Such class of methods focuses on the optimization of trajectories that homogeneously excite the system dynamics in order to attain a robust, well-conditioned linear system during parameters estimation [7–9].

It is important to remark that the subset of BP can be extended by adding independent friction terms. Friction models can be classified into two main categories: (i) Static models where friction torque is strictly dependent on the speed of motion, (ii) dynamics models where friction torque depends on a state function. Examples of static models are Coulomb, viscous, polynomial, Stribeck etc. [10], while examples of dynamics models are [11–13].

As a matter of fact, in many applications industrial robots need higher performance than the ones guaranteed by this class of solutions, in particular, this is true in a *locally* constrained workspace while the optimization technique are often thought to be global [14]. In addition, exciting trajectories, used for the estimation, are fairly different from those commonly used in industrial procedures, *i.e.,* trajectories defined as sets of joined simple geometric entities (*e.g.,* lines and circles), performed at constant regime velocity along the path. Hence, the maximum prediction capacity of this class of algorithms is for a class of trajectories never used in industrial tasks.

In a previous work [15], we proposed a *local* dynamics model parameters estimation method to improve the motor-torque prediction accuracy. Such method notably employs a template-class of trajectories applied in most of the manufacturing tasks, *i.e.,* general trajectories described by a set of discrete poses to be interpolated by the built-in industrial robot motion planner on the basis of global user-tunable parameters (fly-by accuracy, velocity profiles, etc). In fact, it is worth stressing that a *local* dynamics model is less influenced by unmodelled

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phenomena like mechanical backslash and elasticity.

As for the robot dynamics model calibration, even force-control strategies were deeply investigated from researchers with an exhaustive bibliography [16,17]. Although the feasibility of these techniques is experimentally demonstrated and despite the efforts of some robot manufacturer [18,19],[1] it is still difficult to find real industrial applications based on force-control strategies [20]. A primary problem is related to the robustness of control algorithms, often impaired by force sensor drift and to the necessity of frequent re-calibration. Another significant problem involves the purchase cost, which can easily exceed 5000 € only for the force sensor.

Some authors have addressed the development of a model-based virtual force sensors by using the motor information to estimate external forces [21–24]. In these works, the joints torques are obtained (i) by exploiting on-board sensors or (ii) by estimating them from the motor currents. From an industrial point of view, the second approach is more convenient because it allows to reduce the number of the installed sensors, on the contrary, it is not always able to guarantee satisfactory performance. It is clear that, depending on the typology of robot, different dynamics phenomena can appear. In fact, lightweight robots, as in [21], have different friction, backlash and elasticity effects. The proposed methodology will be applied only on conventional industrial robots, where elastic effects and mechanical backlash are not the main dynamics phenomena.

The external forces can be computed by subtracting, from the measure of motors currents, the components related to the inertial and the friction contributions that can be estimated through the dynamics model of the manipulator [25,26]. Obviously, the estimation effectiveness depends on the model accuracy and on the signal-to-noise ratio, which can be considerably high especially for acceleration signals. To avoid the use of acceleration values and to deal with the acceleration signal-to-noise ratio a disturbance-observer methods was proposed in [27] and in [28]. However, these approaches require an appropriate observer gain tuning that could lead to excessively reactive behaviours.

The aim of the paper is to investigate the effective integration of a task-oriented dynamics model calibration [15,29] combined with an estimator of the thermal state of the manipulator [30] to improve the external forces estimation and its usage in real industrial applications. The task-oriented dynamics model calibration is based on a two-stage local calibration criteria that allows to excite and finely estimate all the dynamics phenomena guaranteeing an accurate torques prediction. In addition, the proposed virtual sensor takes into account the estimation of the thermal state of the manipulator to cope with the influence on friction terms. The friction model is considered as linearly dependent on the temperature as in [30].

A suitable *local* excitation of the manipulator dynamics, in task subspace region, is provided by means of an evolutionary genetic-based optimization procedure. The suitable/optimal path is defined as a set of via-points (each via-point has 6 joints positions) interpolated through a virtualization of the real robot motion planner. In this way, the effective template trajectory class is embedded into the optimization algorithm. The inertial terms are excited by high dynamics trajectories (1st optimization stage), while the gravitational and the friction terms have greater (relative) contributions at low velocities and accelerations (2nd optimization stage). For this reason, a two-stage optimization splits the problem by finding two different types of trajectories combined together during the estimation phase.

The paper is organized as follows: Section 2 describes the adopted dynamics model and the developed methodologies to estimate the dynamics model parameters in the workspace sub-region. Trajectory identification and model calibration are addressed in Section 3. Section 4 presents the method for the estimation of the external forces. Section 5 summarizes the overall procedure. Section 6 reports experiments related to the application and the validation of the developed virtual force sensor applied in a polishing task, the proposed algorithm is also compared with other virtual sensors proposed in literature to show its effectiveness. Finally, conclusions are reported in Section 7.

[1] Both of these solutions provide a “force sensor pack”, with force-control functionalities already integrated with the robot controller.

Notation

$\mathbf{q} = [q^1, \ldots, q^n]^T$	$\mathbb{R}^n$ vector of joint positions.
$\mathbf{q}_s, \dot{\mathbf{q}}_s, \ddot{\mathbf{q}}_s, \tau_s$	Vectors of joint positions, velocities, accelerations, and torques at sth sample time.
$\mathbf{Q} \equiv \{\mathbf{q}_1, \ldots, \mathbf{q}_S\}$	Joint position time series of S different sample times.
$\mathbf{Q}, \dot{\mathbf{Q}}, \ddot{\mathbf{Q}}, \mathscr{T}$	Position, velocity, acceleration and torque time series.
$\widetilde{(\cdot)}, \widehat{(\cdot)}, \check{(\cdot)}, (\cdot)^*$	Measured value, estimated value, the root mean square value and the optimum estimation respectively.

2. Manipulator dynamics model

The dynamics of a robot manipulator can be expressed by considering motor torques $\boldsymbol{\tau}$ as the sum of the inertial effects $\boldsymbol{\tau}_i$ and the friction contribution $\boldsymbol{\tau}_f$. The inertial torques component $\boldsymbol{\tau}_i$ can be expressed as

$$\tau_i = \boldsymbol{B}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{G}(\boldsymbol{q}), \tag{1}$$

where $\boldsymbol{B(q)}$, $\boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}})$, and $\boldsymbol{G(q)}$ are, respectively, the inertia matrix, the Coriolis matrix, and the gravitational term.

For open-chain rigid robot, (1) can be rewritten as

$$\tau_i = \boldsymbol{\phi}^b(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\boldsymbol{\pi}^b, \tag{2}$$

where π^b is a subset of dynamics model parameters (also referred to as inertial parameters [3]), even known as BP [31], and the matrix function $\boldsymbol{\phi}^b$ is a generalized acceleration matrix dependent only on the geometry and on the kinematic state of the robotic arm. The BP set π^b includes only combinations of the inertial parameters that are observable along any exciting trajectory that generates $\boldsymbol{\phi}^b$.

A suitable solution to model the joints friction $\boldsymbol{\tau}_f$ is to use the sum of a third order polynomial term (3), thus, for each of the ith robot joints, friction can be expressed as

$$\tau_{fp}^i = [k_0^i + k_1^i|\dot{q}^i| + k_2^i|\dot{q}^i|^2 + k_3^i|\dot{q}^i|^3]\mathrm{sgn}(\dot{q}^i), \tag{3}$$

with an additional Stribeck term

$$\tau_{fs}^i = k_4^i e^{-c_s^i|\dot{q}^i|}\mathrm{sgn}(\dot{q}^i), \tag{4}$$

where parameters $[k_0^i, \ldots, k_4^i]$ are the polynomial coefficients and c_s^i is Stribeck coefficient. Joint torques linearly depend on $[k_0^i, \ldots, k_4^i]$, while c_s^i has a nonlinear influence.

Thus, it possible to write the friction term as

$$\tau_f = \boldsymbol{\phi}^f(\dot{\boldsymbol{q}}, \boldsymbol{c}_s)\boldsymbol{\pi}^f, \tag{5}$$

where $\boldsymbol{\phi}^f(\dot{\boldsymbol{q}}, \boldsymbol{c}_s)$ is the friction regressor and the parameters set π^f defined as

$$\boldsymbol{\pi}^f = [k_0^1 \ldots k_4^1 k_1^2 \ldots k_4^n]^T,$$

Combining (2) and (5), it possible to define the overall torque as

$$\tau = [\boldsymbol{\phi}^b(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) \;\; \boldsymbol{\phi}^f(\dot{\mathbf{q}}, \mathbf{c}_s)]\begin{bmatrix}\boldsymbol{\pi}^b \\ \boldsymbol{\pi}^f\end{bmatrix} = \boldsymbol{\phi}^0(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}, \mathbf{c}_s)\boldsymbol{\pi}^0, \tag{6}$$

where $\boldsymbol{\phi}^0$ is the compound regressor and π^0 is the compound set of dynamics model parameters. However, the assumption of a constant value of π^f over time is in general inappropriated in practice, due to the temperature variations in joints transmission [32].