Interaction Force Computation Exploiting Environment Stiffness Estimation for Sensorless Robot Applications

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***Abstract*—Industrial robots are increasingly used to perform tasks requiring an interaction with the surrounding environment. However, standard controllers require force/torque measurements to close the loop. Most of the industrial manipulators do not have embedded force/torque sensor(s), requiring additional efforts (*i.e.*, additional costs and implementation resources) for such integration in the robotic setup. To extend the use of compliant controllers to sensorless force control, a model-based methodology is presented in this paper. Relying on sensorless Cartesian impedance control, an Extended Kalman Filter (EKF) is proposed to estimate the interaction environment stiffness. Exploiting such estimation, the interaction force can be computed, *e.g.*, to close the force loop, making the sensorless robot able to perform the target task (*e.g.*, probing task, assembly task). The described approach has been validated with experiments. A Franka EMIKA panda robot has been used as a test platform. A probing task involving different materials (*i.e.*, with different - unknown - stiffness properties) has been considered to show the capabilities of the developed EKF. The computed interaction force (on the basis of the estimated environment stiffness) has been compared with the Franka EMIKA panda robot force measurements to prove the effectiveness of the proposed approach.**

***Index Terms*—Extended Kalman Filter, environment stiffness estimation, robot force control, sensorless Cartesian impedance control, Industry 4.0, industrial robots.**

I. Introduction

A. Context

Within the manufacturing context relying on the Industry 4.0 paradigm, robots have to provide a flexible solution, capable to adapt to new tasks and production, while guaranteeing target performance [1]. Considering interaction tasks, the capability to adapt the robot behavior to new scenarios becomes even more critical [2]. Common interaction control strategies, however, make use of expensive sensors to be integrated in the robotic cell [3], increasing the hardware costs and the setup time. To avoid the use of such expensive devices while making the robot able to adapt to uncertain interaction, many works are investigating external wrench estimation algorithms and sensorless control methodologies.

B. Related works

Being able to achieve a sensorless stable interaction dynamics between standard industrial robots (*i.e.*, without joint-level torque sensors and/or end-effector force/torque sensors) and the environment is taking many attentions from the research community. On the one hand, force-sensorless methodologies to estimate the interaction have been proposed [4]–[6]. On the other hand, sensorless methodologies to control the interaction have been proposed [7]–[9]. The described approaches allow to estimate and control the interaction between the robot and the environment only making use of the robot dynamical model, without including the environment dynamics in the modeling/estimation. Such modeling and estimation, however, is of great importance to design the interaction controller [10]. In fact, having an estimation of the environment stiffness improves the control performance [11]. From the state-of-the-art review, the only sensorless approach estimating the environment compliance can be found in [12]. However, the convergence of the method is guaranteed only in the presence of a persistent excitation (*i.e.*, a constant reference force cannot be applied - as for many real industrial tasks, such as assembly tasks).

C. Paper Contribution

Extending the work in [13], the proposed contribution defines a sensorless model-based methodology (considering the robot-environment interaction dynamics) to estimate the interaction environment stiffness. Exploiting such an estimation, the interaction force can be computed to close a force loop, making the sensorless robot able to perform the target interaction tasks (*e.g.*, probing task, assembly task). Relying on sensorless Cartesian impedance control, an Extended Kalman Filter (EKF) is designed to estimate the interaction environment stiffness. This EKF takes into account the nonlinear robot dynamics resulting from the sensorless Cartesian impedance controller, together with the environment dynamics (modeled as a pure elastic system). The main advantage of the proposed approach is that no persistent excitation is required to perform the environment stiffness estimation. The described approach has been validated with experiments, using a Franka EMIKA panda robot as a test platform. A probing task involving different materials with unknown stiffness properties has been considered for the evaluation of the developed EKF. To prove the effectiveness of the estimation, the computed interaction force (exploiting the estimated environment stiffness) has been compared with the Franka EMIKA panda robot force measurements.

II. Robot control

A. Sensorless Cartesian impedance control

To design the proposed sensorless Extended Kalman Filter for the estimation of the interaction environment stiffness, the sensorless Cartesian impedance controller has to be implemented on the robot. The following manipulator dynamics is considered [14]:

$$\mathbf{B}(\mathbf{q})\ddot{\mathbf{q}}+\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})+\mathbf{g}(\mathbf{q})+\boldsymbol{\tau}_f(\dot{\mathbf{q}})=\boldsymbol{\tau}-\mathbf{J}(\mathbf{q})^T\mathbf{h}_{ext}, \quad (1)$$

where $\mathbf{q}$ is the robot joint position vector, $\mathbf{B}(\mathbf{q})$ is the robot inertia matrix, $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})$ is the robot Coriolis vector, $\mathbf{g}(\mathbf{q})$ is the robot gravitational vector, $\boldsymbol{\tau}_f(\dot{\mathbf{q}})$ is the robot joint friction vector, $\mathbf{J}(\mathbf{q})$ is the robot geometric Jacobian matrix, and $\mathbf{h}_{ext}$ is the robot external force/torque vector (*i.e.*, wrench), $\boldsymbol{\tau}$ is the robot joint torque vector.
Based on (1), it is possible to design the sensorless Cartesian impedance controller with dynamics compensation [14], defining the robot joint torque vector $\boldsymbol{\tau}$ as:

$$\boldsymbol{\tau}=\mathbf{B}(\mathbf{q})\boldsymbol{\gamma}+\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})+\mathbf{g}(\mathbf{q})+\boldsymbol{\tau}_f(\dot{\mathbf{q}}), \quad (2)$$

where $\boldsymbol{\gamma}$ is the sensorless Cartesian impedance control law:

$$\boldsymbol{\gamma}=\mathbf{J}(\mathbf{q})^{\#}\left(\ddot{\mathbf{x}}^{imp}-\dot{\mathbf{J}}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}}\right). \quad (3)$$

where $\mathbf{J}(\mathbf{q})^{\#}$ is the pseudo-inverse of the Jacobian matrix. The sensorless Cartesian impedance reference acceleration $\ddot{\mathbf{x}}^{imp}$ is defined as:

$$\ddot{\mathbf{x}}^{imp}=-\mathbf{M}^{-1}\left(\mathbf{D}\dot{\mathbf{x}}+\mathbf{K}\Delta\mathbf{x}\right), \quad (4)$$

where $\mathbf{M}$ is the impedance control mass matrix, $\mathbf{D}$ is the impedance control damping matrix, and $\mathbf{K}$ is the impedance control stiffness matrix (all matrices including translational and rotational components). $\Delta\mathbf{x}=\mathbf{x}-\mathbf{x}^d$, where $\mathbf{x}^d$ is the impedance setpoint and $\mathbf{x}$ is the current robot Cartesian pose. Substituting (4), (3), (2) into (1), the controlled robot dynamics results in:

$$\mathbf{M}\ddot{\mathbf{x}}+\mathbf{D}\dot{\mathbf{x}}+\mathbf{K}\Delta\mathbf{x}=-\overline{\mathbf{L}}(\mathbf{q})\mathbf{h}_{ext}, \quad (5)$$

where $\overline{\mathbf{L}}(\mathbf{q})=\mathbf{M}\mathbf{J}(\mathbf{q})\mathbf{B}(\mathbf{q})^{-1}\mathbf{J}(\mathbf{q})^T$ couples the Cartesian degrees of freedom (DoFs).

B. Redundancy management

The Franka EMIKA panda manipulator has been used as a test platform for experimental validation. Such a robot is redundant, requiring to manage its null-space configuration while performing the main task. In this paper, a pure damping behavior is proposed for the null-space configuration control, aiming to damp the null-space motion:

$$\boldsymbol{\tau}_R=\mathbf{B}(\mathbf{q})\left(\mathbf{I}-\mathbf{J}(\mathbf{q})^{\#}\mathbf{J}(\mathbf{q})\right)\left(-\mathbf{D}_n\dot{\mathbf{q}}\right), \quad (6)$$

where $\boldsymbol{\tau}_R$ is the null-space control torque, $\mathbf{I}$ is the identity matrix, and $\mathbf{D}_n$ is the null-space damping diagonal matrix. The term $\left(\mathbf{I}-\mathbf{J}(\mathbf{q})^{\#}\mathbf{J}(\mathbf{q})\right)$ is the null-space projection matrix. The term $-\mathbf{D}_n\dot{\mathbf{q}}$ allows to damp the null-space motion. Such additional term (6) is therefore included in the control law (2).

III. Sensorless Extended Kalman Filter

The aim of this paper is to propose a sensorless model-based methodology to estimate the interaction environment stiffness along translational directions (only the translational Cartesian DoFs will be considered in the EKF development). The translational dynamics from (5) will be considered:

$$\mathbf{M}_t\ddot{\mathbf{x}}_t+\mathbf{D}_t\dot{\mathbf{x}}_t+\mathbf{K}_t\Delta\mathbf{x}_t=-\overline{\mathbf{L}}(\mathbf{q})\mathbf{f}, \quad (7)$$

where $\mathbf{x}_t$ is the robot Cartesian position vector, $\mathbf{M}_t$ is the translational part of the impedance control mass matrix, $\mathbf{D}_t$ is the translational part of the impedance control damping matrix, $\mathbf{K}_t$ is the translational part of the impedance control stiffness matrix, and $\mathbf{f}$ is the external force vector. $\Delta\mathbf{x}_t=\mathbf{x}_t-\mathbf{x}_t^d$, where $\mathbf{x}_t^d$ is the impedance setpoint along translational directions.

A. Interaction environment dynamics modeling

In order to design the EKF to be used for the estimation of the interaction environment stiffness, the interaction environment dynamics has to be modeled. Based on [13], the simplest way to describe the interaction environment dynamics is the linear spring-damper model (with environment position vector $\mathbf{x}_e$, stiffness matrix $\mathbf{K}_e$, and damping matrix $\mathbf{D}_e$):

$$\sum_i(\mathbf{D}_e^i\dot{\mathbf{x}}_e^i+\mathbf{K}_e^i\mathbf{x}_e^i)=\mathbf{f}, \quad \forall i=1,\cdot\cdot,N, \quad (8)$$

for all the finite number N of interaction ports.

Considering the translational Cartesian DoFs and under the hypothesis of a stable single contact point (*i.e.*, the robot and the environment are always in contact with $\mathbf{x}_e=\mathbf{x}_t$) and considering that the damping $\mathbf{D}_e$ does not affect the stiffness estimation at steady-state, (8) can be written as follows (considering a pure elastic environment dynamics):

$$\mathbf{K}_e\mathbf{x}_t=\mathbf{f}. \quad (9)$$

By substituting (9) in (7), the coupled robot-environment interaction dynamics can be defined as:

$$\overline{\mathbf{M}}_t\ddot{\mathbf{x}}_t+\overline{\mathbf{D}}_t\dot{\mathbf{x}}_t+\overline{\mathbf{K}}_t(\mathbf{q})\mathbf{x}_t=\mathbf{K}_t\mathbf{x}_t^d, \quad (10)$$

where $\overline{\mathbf{M}}_t=\mathbf{M}_t$, $\overline{\mathbf{D}}_t=\mathbf{D}_t$, $\overline{\mathbf{K}}_t(\mathbf{q})=\mathbf{K}_t+\overline{\mathbf{L}}(\mathbf{q})\mathbf{K}_e$. It has to be underlined that the equivalent stiffness matrix $\overline{\mathbf{K}}_t(\mathbf{q})$ is a function of the joint position $\mathbf{q}$.

B. Extended Kalman Filter design

Exploiting the coupled robot-environment dynamic equation (10), it is possible to design the EKF to be used for the estimation of the interaction environment stiffness $\mathbf{K}_e$.
The robot-environment interaction dynamics can be defined by the following filter state $\mathbf{x}_a$ composed by the robot velocity $\dot{\mathbf{x}}_t$ and position $\mathbf{x}_t$ states, and augmented with the environment stiffness properties $\mathbf{K}_e$:

$$\mathbf{x}_a = [\dot{\mathbf{x}}_t, \mathbf{x}_t, \mathbf{K}_e]^T. \tag{11}$$

Substituting the augmented state $\mathbf{x}_a$ (11) in the interaction dynamics model (10), the filter dynamics result in:

$$\mathbf{f}(\mathbf{x_a}, \boldsymbol{\nu}_\mathbf{a}) = \begin{bmatrix} \ddot{\mathbf{x}}_t \\ \dot{\mathbf{x}}_t \\ \dot{\mathbf{K}}_e \end{bmatrix} = \begin{bmatrix} \overline{\mathbf{M}}_t^{-1} \left(-\overline{\mathbf{D}}_t \dot{\mathbf{x}}_t - \overline{\mathbf{K}}_t(\mathbf{q})\mathbf{x}_t + \mathbf{K}_t \mathbf{x}_t^d + \boldsymbol{\nu}_{\mathbf{x}_t}\right) \\ \dot{\mathbf{x}}_t + \overline{\mathbf{M}}_t^{-1} \boldsymbol{\nu}_{\dot{\mathbf{x}}_t} \\ \boldsymbol{\nu}_{\mathbf{K}_e} \end{bmatrix}, \tag{12}$$

where the vector $\boldsymbol{\nu}_a = [\boldsymbol{\nu}_{\mathbf{x}_t}, \boldsymbol{\nu}_{\dot{\mathbf{x}}_t}, \boldsymbol{\nu}_{\mathbf{K}_e}]^T$ accounts for uncertainties in models parameters/estimates.
The observer of the augmented state is therefore defined as:

$$\begin{cases} \dot{\widehat{\mathbf{x}}}_a = \mathbf{f}(\mathbf{x_a}, \boldsymbol{\nu}_\mathbf{a}) + \mathbf{K}_{EKF}(\mathbf{y} - \mathbf{C}_a \widehat{\mathbf{x}}_a), \\ \widehat{\mathbf{y}} = \mathbf{h}(\mathbf{x_a}, \mathbf{w}), \end{cases} \tag{13}$$

with $\widehat{\mathbf{x}}_a$ the augmented state estimate, $\mathbf{C}_a$ the observation matrix for the robot velocity $\dot{\mathbf{x}}_t$ and the robot position $\mathbf{x}_t$ (*i.e.*, $\mathbf{y} = [\dot{\mathbf{x}}_t, \mathbf{x}_t]^T$), and $\mathbf{K}_{EKF}$ the gain matrix:

$$\mathbf{K}_{EKF} = \mathbf{P}\mathbf{C}_a\mathbf{R}^{-1}. \tag{14}$$

$\mathbf{R}$ is the measurement noise matrix defined as:

$$\mathbf{R} = \mathbf{H}E\{\mathbf{w}\mathbf{w}^T\}\mathbf{H}^T = \mathbf{H}\mathbf{W}\mathbf{H}^T, \tag{15}$$

where the observation function $\mathbf{h}$ linearly maps the sample inaccuracies, due to measurement noise $\mathbf{w}$, through the matrix $\mathbf{H}$:

$$\mathbf{H} = \left.\frac{\partial \mathbf{h}}{\partial \mathbf{w}}\right|_{\widehat{\mathbf{x}}_a}. \tag{16}$$

The covariance matrix $\mathbf{P}$ and its rate, as in:

$$\dot{\mathbf{P}} = \mathbf{A}_a\mathbf{P} - \mathbf{P}\mathbf{C}_a^T\mathbf{R}^{-1}\mathbf{C}_a\mathbf{P} + \mathbf{Q} + \mathbf{P}\mathbf{A}_a^T, \tag{17}$$

are based on the dynamics of the state and the model uncertainties, defined with matrix $\mathbf{A}_a$ and matrix $\mathbf{G}_a$ respectively:

$$\mathbf{A}_a = \left.\frac{\partial \mathbf{f}}{\partial \mathbf{x}_a}\right|_{\widehat{\mathbf{x}}_a}; \qquad \mathbf{G}_a = \left.\frac{\partial \mathbf{f}}{\partial \boldsymbol{\nu}_a}\right|_{\widehat{\mathbf{x}}_a}, \tag{18}$$

and on matrix $\mathbf{Q}$ used for the estimation of the parameters, which is defined as:

$$\mathbf{Q} = \mathbf{G}_a E\{\boldsymbol{\nu}_a\boldsymbol{\nu}_a^T\}\mathbf{G}_a^T = \mathbf{G}_a\mathbf{V}\mathbf{G}_a^T. \tag{19}$$

It has to be underlined that in the filter dynamics (12) the equivalent stiffness matrix $\overline{\mathbf{K}}_t(\mathbf{q})$ appears as a function of the joint position $\mathbf{q}$ (due to $\mathbf{J}(\mathbf{q})$ and $\mathbf{B}(\mathbf{q})$). When the robot is in interaction with an environment while executing a task, its joint configuration is not excessively modifying, or this is happening with a dynamics much slower than the interaction dynamics. It is therefore possible to neglect the time-derivative $\dot{\overline{\mathbf{K}}}_t(\mathbf{q})$ in (18), considering the constant matrix $\overline{\mathbf{K}}_t(\overline{\mathbf{q}})$. In such a way, (12) can be written as follows:

$$\mathbf{f}(\mathbf{x_a}, \boldsymbol{\nu}_\mathbf{a}) = \begin{bmatrix} \ddot{\mathbf{x}}_t \\ \dot{\mathbf{x}}_t \\ \dot{\mathbf{K}}_e \end{bmatrix} = \begin{bmatrix} \overline{\mathbf{M}}_t^{-1} \left(-\overline{\mathbf{D}}_t \dot{\mathbf{x}}_t - \overline{\mathbf{K}}_t(\overline{\mathbf{q}})\mathbf{x}_t + \mathbf{K}_t \mathbf{x}_t^d + \boldsymbol{\nu}_{\mathbf{x}_t}\right) \\ \dot{\mathbf{x}}_t + \overline{\mathbf{M}}_t^{-1} \boldsymbol{\nu}_{\dot{\mathbf{x}}_t} \\ \boldsymbol{\nu}_{\mathbf{K}_e} \end{bmatrix}. \tag{20}$$

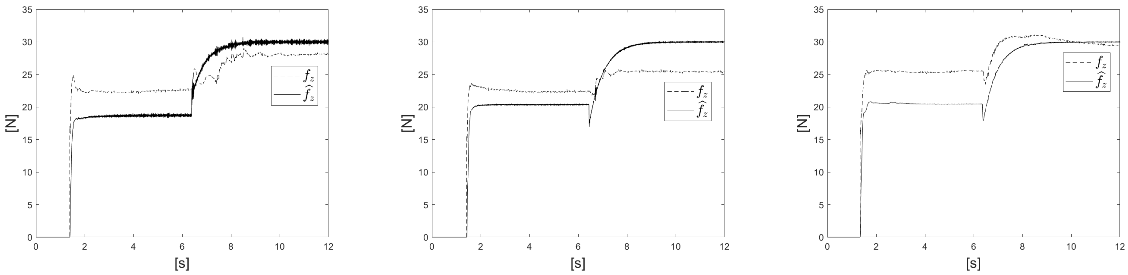
The approximation of $\overline{\mathbf{K}}_t(\mathbf{q})$ in $\overline{\mathbf{K}}_t(\overline{\mathbf{q}})$ introduces negligible modeling errors, that are of orders of magnitude smaller than common modeling errors resulting from the robot dynamics identification procedures.

IV. Experimental results

A Franka EMIKA panda manipulator has been used as a test platform. The controller (2) plus the redundancy management term (6) have been implemented, without the compensation of the joint friction term (currently under development):

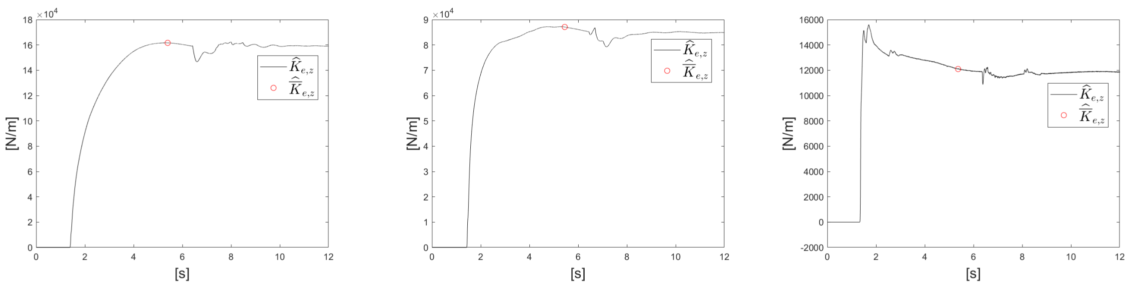
$$\boldsymbol{\tau} = \mathbf{B}(\mathbf{q})\boldsymbol{\gamma} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}) + \mathbf{g}(\mathbf{q}) + \boldsymbol{\tau}_R.$$

A probing task (with different interacting environments, *i.e.*, different stiffness) has been considered as a reference task. The interaction is established along the z Cartesian DoF.
Three different environments with different (unknown) stiffness have been tested. The impedance control matrices have been imposed as follows: mass parameters into the diagonal matrix $\mathbf{M}$ have been imposed equal to 5 kg, while inertia parameters have been imposed equal to 5 kg m^2; translational parameters into the diagonal stiffness matrix $\mathbf{K}$ have been imposed equal to 5000 N/m, while rotational parameters have been imposed equal to 8000 Nm/rad; damping ratio parameters into the diagonal matrix $\mathbf{h}$ have been imposed equal to 1 (allowing for the definition of the damping matrix $\mathbf{D} = 2\mathbf{h}\sqrt{\mathbf{MK}}$).
In the proposed experiments, the robot moves along the Cartesian DoF $-z$ until the contact with the environment is detected. After the contact establishment, the impedance control set-point $x_{t,z}^d = x_{t,z} + 0.0075\,\text{m}$ is applied (also used in the EKF dynamics formulation in (20)). The estimation of the environment stiffness $\widehat{K}_{e,z}$ is used to compute the robot-environment interaction force $\widehat{f}_z$. After the convergence of $\widehat{K}_{e,z}$ to $\widehat{\widehat{K}}_{e,z}$ (*i.e.*, after four seconds from the activation of the EKF), the interaction force estimation $\widehat{f}_z$ is performed using the constant value $\widehat{\widehat{K}}_{e,z}$. $\widehat{f}_z$ is used to close a force-loop defining the impedance control set-point as a *PI* force controller. A reference force $f_z^d = 30N$ has been imposed in the experiments. Such definition of the impedance control set-point is updated in (20) to continuously estimate $\widehat{K}_{e,z}$.
Figure 1 shows the estimated interaction force $\widehat{f}_z$ vs. the measured interaction force f_z for the three environments. Figure 2 shows the estimated interaction environment stiffness $\widehat{K}_{e,z}$ and its converged value $\widehat{\widehat{K}}_{e,z}$ for the three environments. Since $\widehat{f}_z$ is performed with limited errors w.r.t. f_z, $\widehat{K}_{e,z}$ is assumed to be correct with limited uncertainties. Estimation performance can be improved including friction compensation in the controller.



$\widehat{f}_z^1$ vs. f_z^1 $\qquad$ $\widehat{f}_z^2$ vs. f_z^2 $\qquad$ $\widehat{f}_z^3$ vs. f_z^3

Fig. 1: Estimated interaction force $\widehat{\mathbf{f}}$ (continuous line) vs. measured interaction force $\mathbf{f}$ (dashed line) for the three experimental scenarios.



$\widehat{K}_{e,z}^1$ $\qquad$ $\widehat{K}_{e,z}^2$ $\qquad$ $\widehat{K}_{e,z}^3$

Fig. 2: Estimated interaction environment stiffness $\widehat{K}_{e,z}$ and its converged value $\widehat{\overline{K}}_{e,z}$ for the three experimental scenarios.

In fact, without including friction compensation, modeling errors are shown in (10), decreasing the estimation performance of (20). In addition, the continuous update of $\widehat{K}_{e,z}$ can be exploited instead of $\widehat{\overline{K}}_{e,z}$ for the computation of $\widehat{f}_z$, capturing changes of the interacting environment stiffness (*e.g.*, due to non-linearities).

V. Conclusions

The presented paper proposed a sensorless model-based methodology to estimate the interaction environment stiffness. Exploiting the estimation provided by the proposed EKF, the interaction force can be computed, making the sensorless robot able to perform interaction tasks. The described approach has been validated in a probing task with experiments, using the Franka EMIKA panda manipulator. Current/future work is devoted to improve the estimation accuracy developing high-performance friction compensation. In addition, the design of sensorless force control exploiting the proposed framework is under investigation (considering optimal control). Machine learning techniques are also considered for the offline tuning of the EKF gains and of the sensorless force controller gains.

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