LINK-SIC — Industrial Robotics Projects

Performance of ILC applied to a flexible mechanical system

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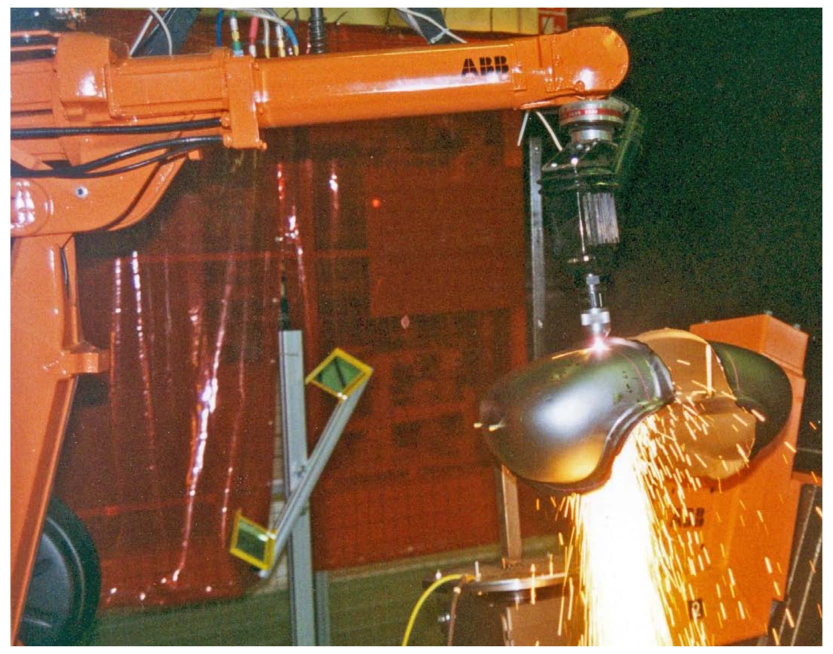
Summary

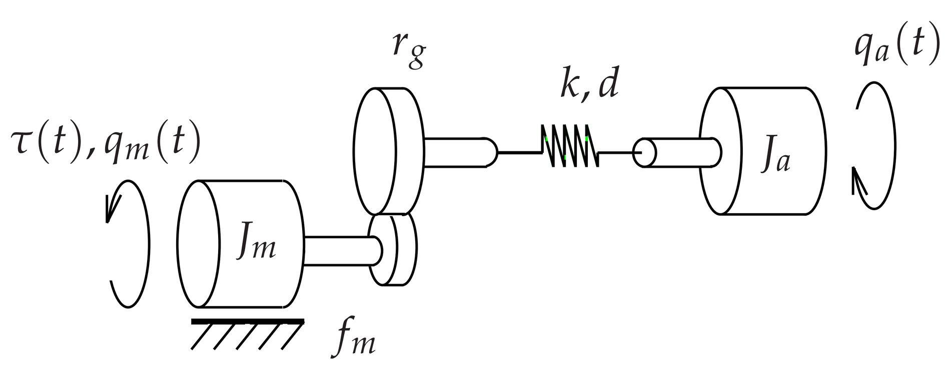
Iterative learning control (ILC) is applied to a flexible two-mass system representing an idealised model of a robot joint. The motor angle (first mass) is the measured variable and the tool angle (second mass) is the controlled variable. Robustness and performance aspects regarding the tool angle are discussed, when the ILC algorithm is based on only the measured motor angle or the estimated tool angle.

Problem

ILC is traditionally applied to systems where the controlled variable is the measured variable. However, in standard industrial robots only the motor angles are measured, while the control objective is to follow a tool path.



A modern industrial robot is flexible. Assuming that the mechanical flexibilities are concentrated to the robot joints, the two-mass model can approximately describe a single joint.

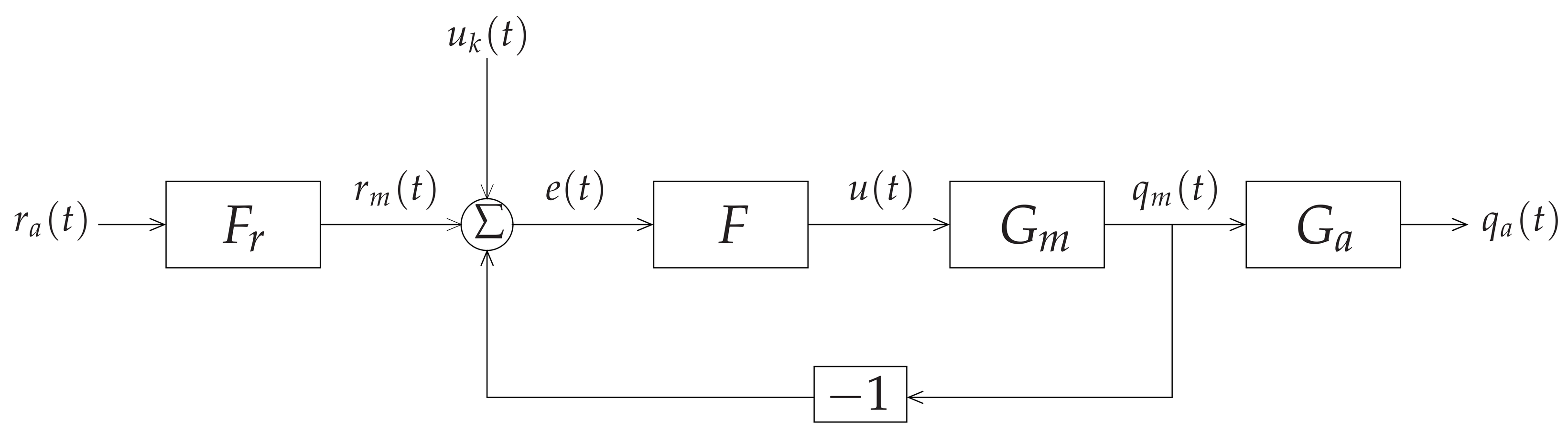


Set-up for the simulation

Generally the tool-angle reference $r_a(t)$ is given by the application. Here it is chosen as a filtered step. The corresponding motor-angle reference $r_m(t)$ is

$$r_m(t) = F_r(q)r_a(t).$$

The system is controlled by the controller F. The ILC algorithm thereby works as a complement to the ordinary controller. In the block diagram the ILC update $u_k(t)$ is added to $r_m(t)$.



ILC algorithm

The discrete-time system is generally formulated as

$$y_k(t) = T_r(q)r(t) + T_u(q)u_k(t),$$

with the system output $y_k(t)$, ILC input signal $u_k(t)$ and reference $r(t)$. The update for a first-order ILC algorithm is given by

$$u_{k+1}(t) = Q(q)\big(u_k(t) + L(q)e_k(t)\big), \qquad e_k(t) = r(t) - y_k(t).$$

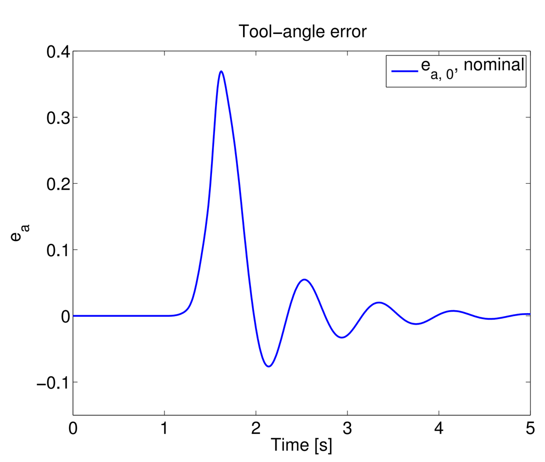
The update implies the standard frequency-domain convergence criterion

$$|1 - L(e^{i\omega})T_u(e^{i\omega})| < |Q^{-1}(e^{i\omega})|, \quad \forall\omega.$$

A P-ILC algorithm is applied to the flexible two-mass model, with

- Q is chosen as a low-pass second-order Butterworth filter with a cutoff frequency above the bandwidth of the controlled system.
- $L = \gamma q^{\delta}$.

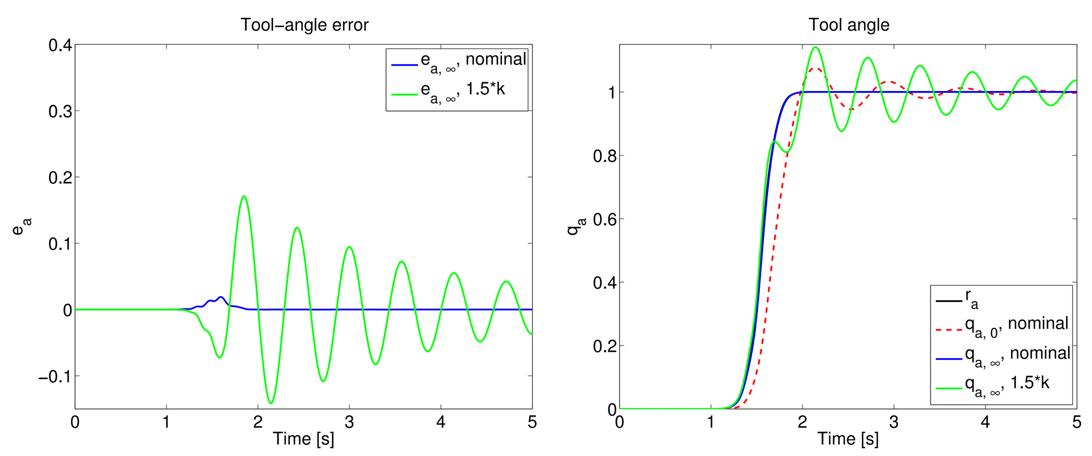
Results



Model errors are introduced; incorrect tool mass (J_a) and uncertain gearbox stiffness (k). Robustness and performance aspects regarding the tool angle are discussed, when the ILC algorithm is based on different measurements. Initial tool-angle errors without ILC are shown in the figure.

The ILC algorithm using $e_m(t) = r_m(t) - q_m(t)$

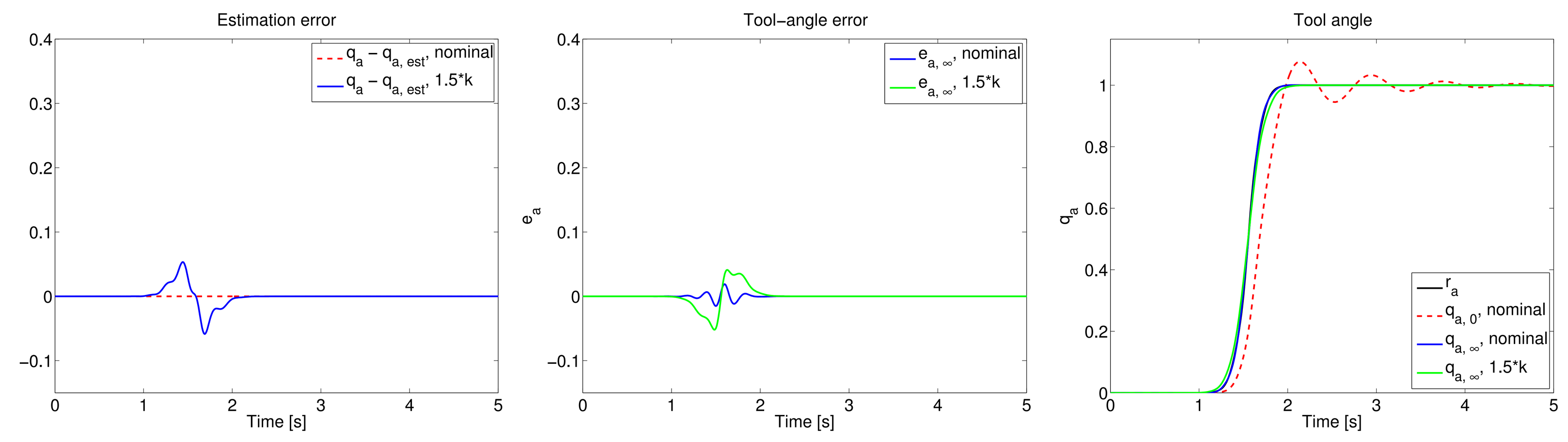
The ILC algorithm is robust with respect to model errors. However, the tool performance is sensitive with respect to F_r — the tool angle converges towards the incorrect signal when model errors are introduced.



The ILC algorithm using $e_a(t) = r_a(t) - \hat{q}_a(t)$

Using motor torque $\tau(t)$ and measurements of the motor angle $q_m(t)$, the tool angle is estimated by a discrete-time Kalman filter, giving $\hat{q}_a(t)$.

The tool-angle error is significantly reduced both for the nominal case and in the case of large model errors, compared to the initial error. The error reduction is notable, since the ILC update uses the estimated tool angle $\hat{q}_a(t)$, with the estimation error $q_a(t) - \hat{q}_a(t)$.



Conclusions

- ✘ An ILC update, based on an estimate of the tool angle, reduces the final tool-angle error after convergence significantly compared to the initial error without ILC. This is the case even though large model errors are introduced.
- ✘ The ILC update, based on the motor-angle error, is more sensitive to model errors than when using an estimate of the tool angle in the update. This can be explained by the fact that the motor-angle reference is computed using the inverse of the nominal system relating motor angle to tool angle.