MIMO ILC using complex kernel regression: An application to precision SEA robots

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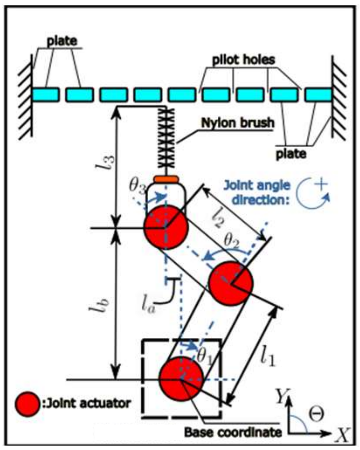
Abstract

This work[1] shows around 90% improvement in the positioning precision for local, repeated and high-speed hole-cleaning task executed by lightweight robots with series elastic actuators (SEAs), through iterative learning control(ILC), in which the inputs are updated based on the tracking error and a nonparametric local MIMO model obtained via complex kernel Gaussian process regression (GPR).



Experimental platform info

- > HEBI X5-4 SEAs are used at each joint
- > A flexible brush with bristle diameter 1.25 inch was attached at the end effector
- > MATLAB interface with HEBI libraries were used for communication and control
- > The sampling rate is 100 hz for both inputs and outputs.

Fig.1, Schematic drawing (left) and top view (right) of the experimental SEA robot. The cleaning task for a specific pilot hole consists of letting the brush achieve a periodic forward-and-backward motion with stroke length d, which should be perpendicular to the plate, i.e., the end-effector orientation $\Theta = \pi/2$ rad. The controlled outputs are the local joint angles $\theta_1, \theta_2, \theta_3$.

Inversion-based ILC

Given a linear time-invariant system (LTI) with transfer function $S(\omega)$, an inversion-based ILC is proposed to find the input $I_d(\omega)$ that yields exact tracking of the desired output $O_d(\omega)$. And the iterative update law is

$$I_{k+1}(\omega) = I_k(\omega) + \hat{S}^{\dagger}(\omega)\rho(\omega)(O_d(\omega) - O_k(\omega))$$

where subscripts denote the iteration number and $\hat{S}^{\dagger}(\omega)$ is the input-weighted pseudo-inverse of the estimated model $\hat{S}(\omega)$. And the diagonal iteration gain matrix $\rho(\omega)$ are designed to guarantee the convergence of the tracking error according to the model estimation error

$$\delta(\omega) = S(\omega) - \hat{S}(\omega)$$

Desired trajectory in Y direction

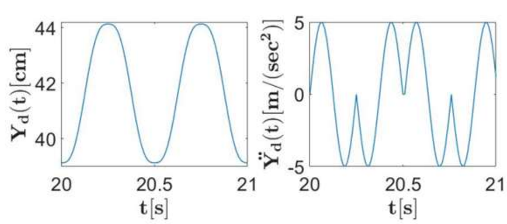


Fig.2, Desired motion Y_d (left) and acceleration $\ddot{Y}_d$ (right) of the brush tip in the Y direction during $t \in [20,21]\ s$

ILC error convergence

The maximum error $\overline{E}$ for each joint from iteration 0 to 10:

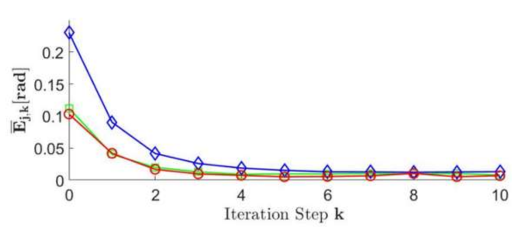


Fig.3, Reduction of joint error $\overline{E}_{j,k}$ with iteration step k: $\overline{E}_{1,,k}$(square), $\overline{E}_{2,,k}$(diamond) and $\overline{E}_{3,,k}$(circle).

$$\overline{E}_{j,k} = \max_t \left|\overline{E}_{j,k}(t)\right| = \max_t \left|O_{j,d}(t) - O_{j,k}(t)\right|$$

Tracking performance

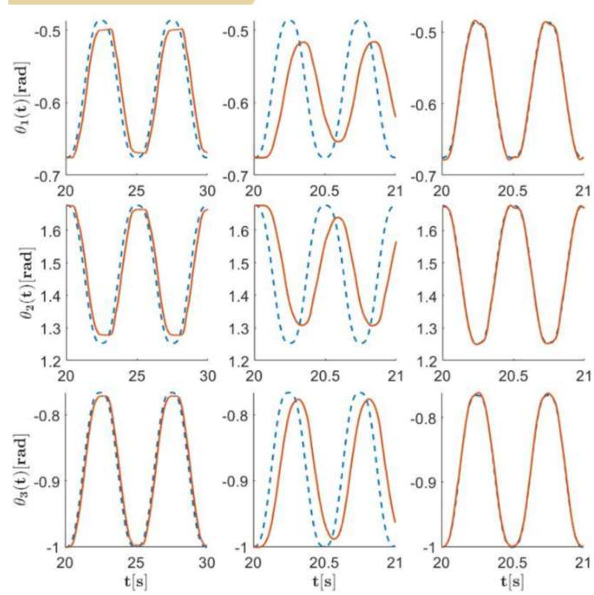


Fig.4, Comparison of desired output O_d (dashed line) and achieved output O (solid line) with and without ILC for three cases: (left) slower trajectories with time period $T = 5s$ without ILC; (middle) faster trajectories with time period $T = 0.5s$ without ILC; and (right) faster trajectories with time period $T = 0.5s$ with ILC.

[1] Yan, L. L., Banka, N., Owan, P., Piaskowy, W. T., Garbini, J. L., & Devasia, S. (2021). MIMO ILC using complex-kernel regression and application to Precision SEA robots. *Automatica*, *127*, 109550.

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