Learning control for positionally controlled manipulators

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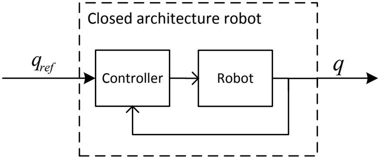
September 11, 2013

Centre of Research Excellence
for Advanced Cooperative Systems

Problem statement

- Closed architecture robotic arms



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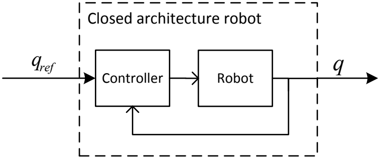

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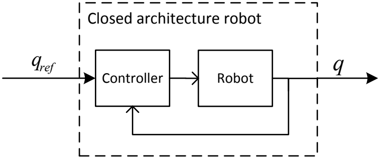

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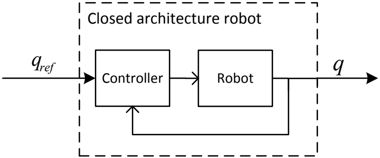

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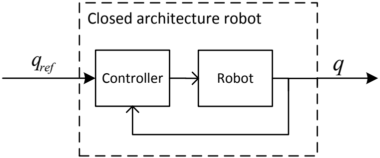

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- Performance degrades for fast trajectories

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- Use learned model for control to achieve better performance

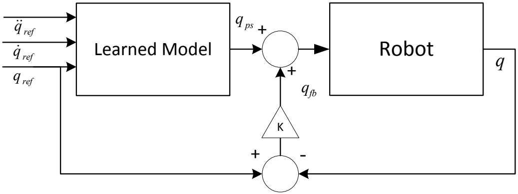

Figure: Nonlinear feedforward control strategy

Our system

- 6 DOF robotic arm

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Figure: Puma 560 robotic arm
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Figure: Puma 560 robotic arm
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  - separate PD control of every joint

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- Random samples from the joint state space for data collection

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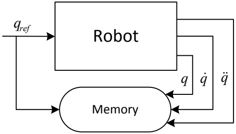

Figure: Data collection

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where

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- Optimization of log marginal likelihood - $\log p(\mathbf{Y}|\mathbf{X})$

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- Incremental SSGP [Gijsberts 2013]
- Update is $\mathcal{O}(1)$ (can run forever)

Results

Offline identification and timing

Table: Inverse model identification for the simulated Puma 560 robotic manipulator

Method	m	n	n_{test}	Mean	Std. dev.	RMS error	Training time
GPR	-	15000	5000	$3.1623e-04$	$7.4755e-04$	$8.1162e-04$	12 [h]
SSGPR fix	100	15000	5000	0.0103	0.0462	0.0173	92 [s]
SSGPR fix	300	15000	5000	0.0069	0.0310	0.0129	495 [s]
SSGPR fix	500	15000	5000	0.0038	0.0250	0.0167	742 [s]
SSGPR fix	800	15000	5000	0.0016	0.0126	0.0089	1444 [s]
SSGPR fix	1000	15000	5000	0.0009	0.0181	0.0056	18029 [s]
SSGPR fix	2000	15000	5000	0.0002	0.0089	0.0014	51054
SSGPR full	100	15000	5000	0.0094	0.0125	0.0156	142 [s]
SSGPR full	500	15000	5000	0.0006	0.0020	0.0021	1624 [s]

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Closed loop control

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- For the i^{th} joint we have

$$q_i(k) = \sum_{l=1}^{N_i} \left(a_l^i \sin(\omega_f lkT_s) - b_l^i \sin(\omega_f lkT_s) \right) \tag{5}$$

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- Analytically differentiable

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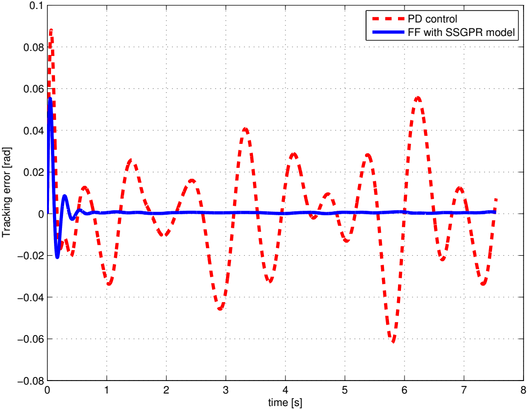

Figure: Joint 1 tracking error comparison

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Closed loop control

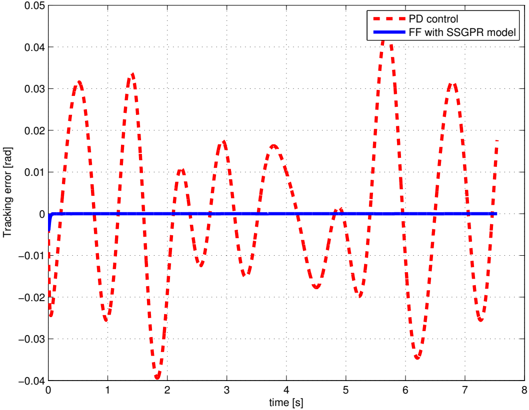

Figure: Joint 4 tracking error comparison

Results

Closed loop control

Table: Closed loop performance of PD and Feedforward control approaches

Value	Joint 1	Joint 2	Joint 3	Joint 4	Joint 5	Joint 6
FF mean	$2.599e-3$	$2.556e-3$	$645.168e-6$	$112.460e-6$	$98.753e-6$	$101.983e-6$
PD mean	$28.775e-3$	$35.688e-3$	$22.342e-3$	$20.979e-3$	$20.845e-3$	$20.430e-3$
FF std. dev	$1.674e-3$	$1.996e-3$	$409.393e-6$	$77.7326e-6$	$77.433e-6$	$80.513e-6$
PD std. dev.	$5.717e-3$	$6.381e-3$	$3.828e-3$	$2.799e-3$	$2.859e-3$	$3.125e-3$

Results

On-line adaptation

Table: One-step prediction errors for different trajectories. Trajectories are ordered by how much they differ from the training state space

Method	GPR	SSGPR	ISSGPR
Trajectory 1	7.9×10^{-9}	0.0011	3.2×10^{-4}
Trajectory 2	6.5×10^{-8}	0.0016	8.7×10^{-4}
Trajectory 3	369.1862	0.1985	0.0036

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Figure: Schunk LWA 4.6

Thank you for your attention

Questions?