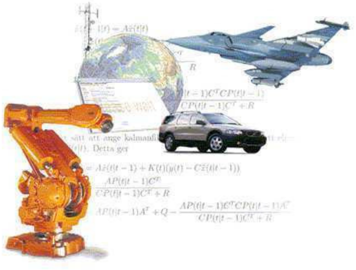
Estimation-based ILC using Particle Filter with Application to Industrial Manipulators



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2. Estimation-based ILC
3. Bayesian Estimation Methods
4. Models
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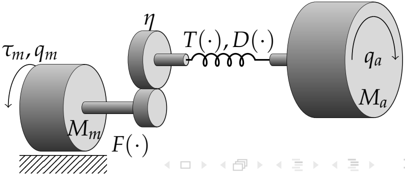

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- The mechanical structure has become less rigid due to cost reduction.
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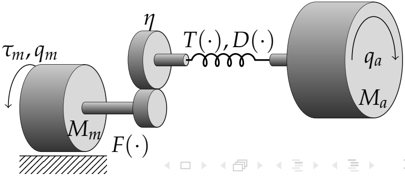
- The joint position q_a deviates from the actuator position q_m.
- To achieve better performance, the joint position q_a has to be measured directly or estimated.

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- Here, the iterative learning control (ILC) method is improved using the estimated joint position.
- ILC is a way to improve the performance of systems that perform the same task repeatedly, e.g. an industrial manipulator performing welding or cutting.
- ILC control law update

$$u_{k+1}(t) = f(u_k(t), r(t), z_k(t))$$

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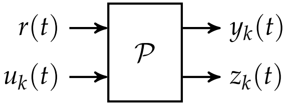
- Instead, $z_k(t)$ has to be estimated.
- Possible to estimate $z_k(t)$ from internal signals.



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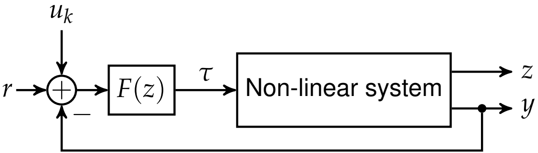

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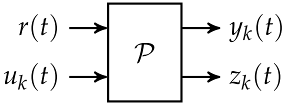
- The following ILC algorithm is used

$$u_{k+1}(t) = \mathcal{Q}(q)\big(u_k(t) + \mathcal{L}(q)\epsilon_k(t)\big), \quad \epsilon_k(t) = r(t) - \hat{z}_k(t)$$
$$\mathcal{L}(q) = \gamma q^{\delta}, \quad \mathcal{Q}(q) = n\text{th order Butterworth filter}$$



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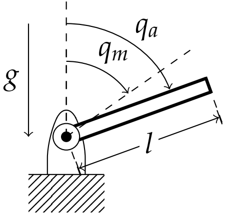
  - Particle filter (PF)
    - Approximate the posterior distribution with a large number of particles.
    - Can handle non-Gaussian noise.

- Flexible single joint model with
  - Linear damping
  - Nonlinear spring
  - Nonlinear friction
- The state vector $\mathbf{x} = \begin{pmatrix} q_a & q_m & \dot{q}_a & \dot{q}_m \end{pmatrix}^T$ gives a continuous-time nonlinear state space model

$$\dot{\mathbf{x}} = \widetilde{f}(\mathbf{x}, \tau)$$



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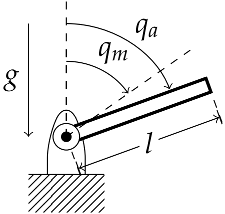
- A discrete-time state space model using Euler sampling according to

$$\mathbf{x}_{t+1} = \mathbf{x}_t + T_s \widetilde{f}(\mathbf{x}_t, \tau_t + w_t) = f(\mathbf{x}_t, \tau_t, w_t)$$

- The process noise $w \sim \mathcal{N}(0, Q)$ enters the model in the same way as the motor torque.



Observation Model (I/II)

- Measure the motor angle q_m and acceleration of the tool position $a_{\mathsf{TCP}} = l\ddot{q}_a$.
- The measurement noise resembles quantization errors

$$e = \begin{cases} -\zeta, & \text{with probability } 1/3 \\ 0, & \text{with probability } 1/3 \\ \zeta, & \text{with probability } 1/3 \end{cases}$$

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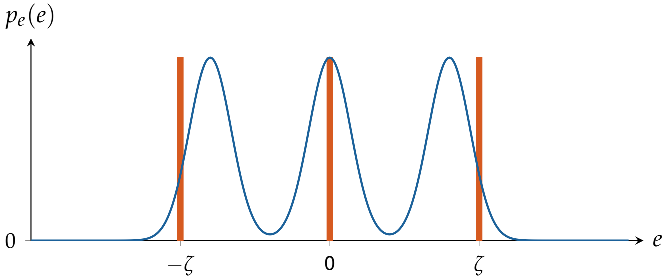
- The PF uses the model

$$p_e(e) = \sum_{i=1}^{3} \frac{1}{3} \mathcal{N}(e | \mu_i, \sigma^2), \quad \mu_i \in \{-0.8\zeta, 0, 0.8\zeta\}$$

- The EKF and UKF uses a Gaussian approximation of $p_e(e)$.

Measurement noise distribution



Red – True noise distribution

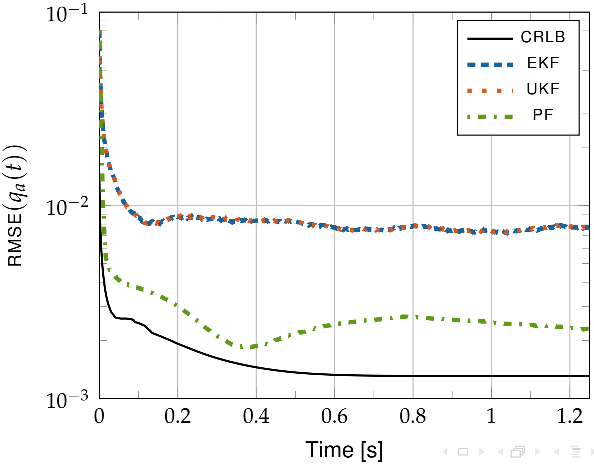
Blue – Modelled noise distribution

- The reference $r(t)$ is a step filtered four times through a FIR filter of order 100.
- The model is unstable, hence a feedback loop is required.
- Filter performance evaluated using the RMSE over 1000 MC simulations and compared to the CRLB.
- ILC performance evaluated using the relative reduction error

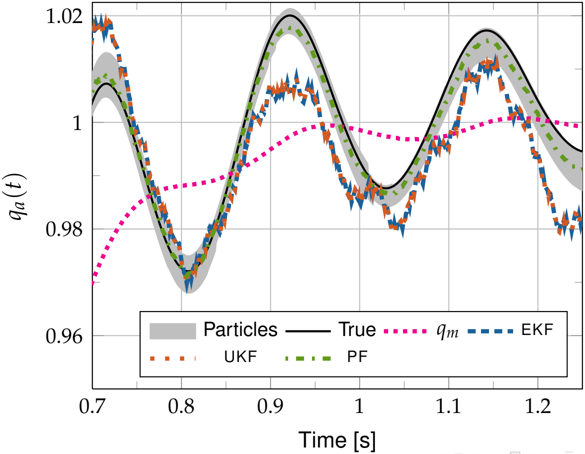
$$\rho_k = 100\frac{||\varepsilon_k(t)||_2}{||\varepsilon_0(t)||_2}$$

averaged over 100 MC simulations.

Root mean square error (RMSE) for q_a over 1000 MC simulations.

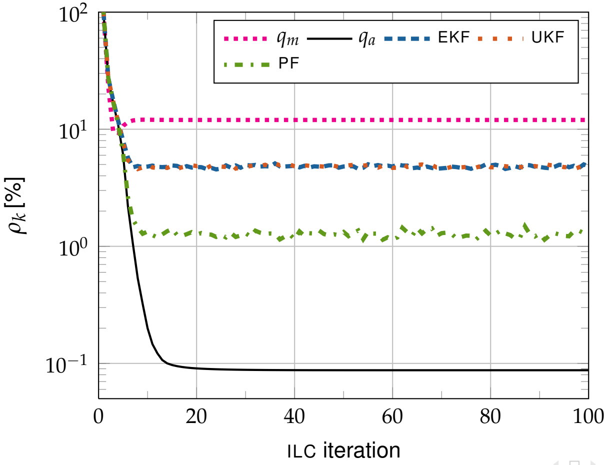


Estimated q_a and the q_m expressed on the arm side of the gearbox.



ILC Performance

Relative reduction error averaged over 100 MC simulations.



Final error [%]

q_m	12.00
q_a	0.088
EKF	4.79
UKF	4.82
PF	1.27

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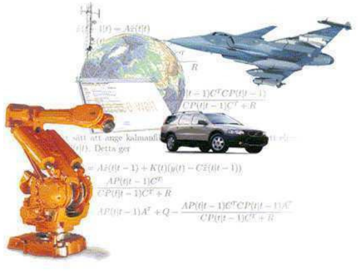

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