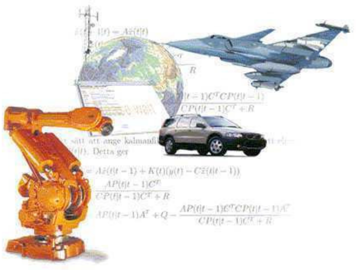
Evaluation of Six Different Sensor Fusion Methods for an Industrial Robot using Experimental Data



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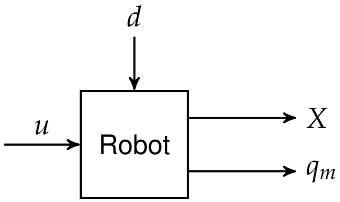
Outline

1. Introduction
   - Problem Formulation
   - Bayesian Estimation
2. Modelling
   - Robot Model
   - Accelerometer Model
   - Estimation Models
3. Experimental Results

Problem Formulation



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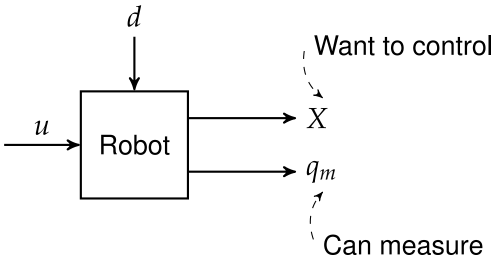

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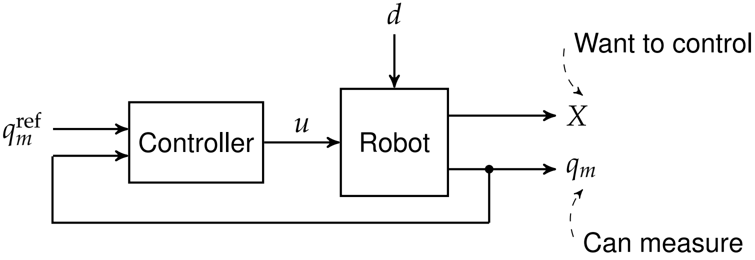

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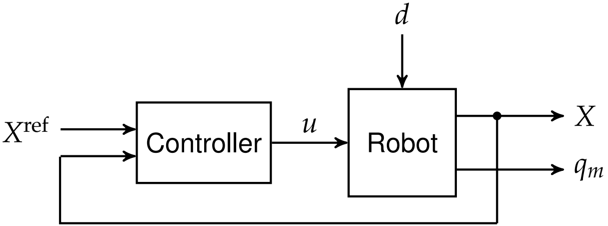

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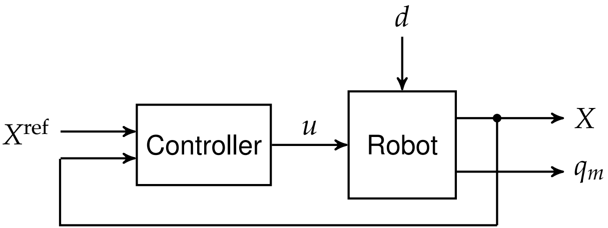

- Want to control the TCP. Can only measure the motor angles q_m.
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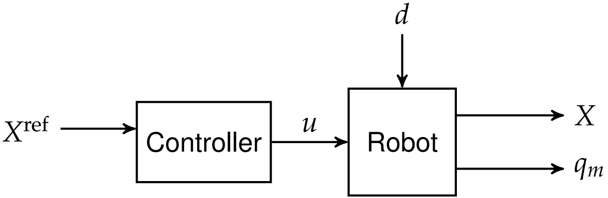
What can we do instead of measuring the TCP?

Problem Formulation



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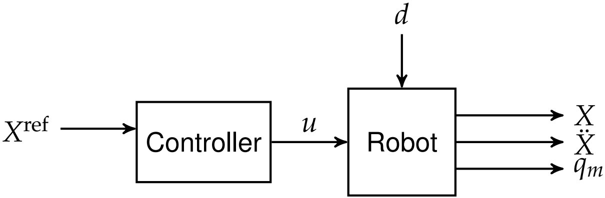
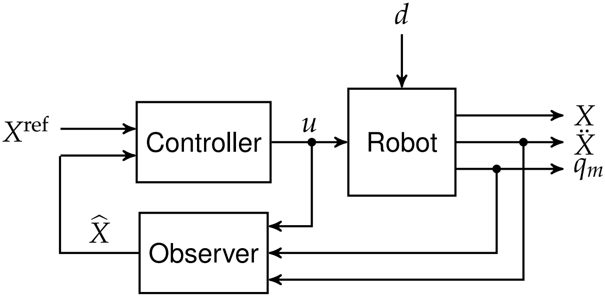


- Let the acceleration of the tool be a measurement.



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- Use an observer to estimate the TCP.

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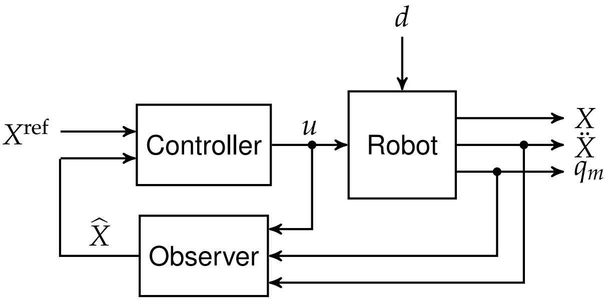

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How can we estimate the TCP?

Bayesian State-space Estimation

Model:

$$x_{k+1} = f(x_k, u_k, w_k),$$
$$y_k = h(x_k) + e_k.$$

Bayesian inference:

$$p(x_{k+1}|y_{1:k}) = \int_{\mathbb{R}^n} p(x_{k+1}|x_k)p(x_k|y_{1:k})\,\mathrm{d}x_k,$$
$$p(x_k|y_{1:k}) = \frac{p(y_k|x_k)p(x_k|y_{1:k-1})}{p(y_k|y_{1:k-1})}.$$

- The Kalman filter is the optimal choice for linear models.
- Approximative filters have to be used for nonlinear models.

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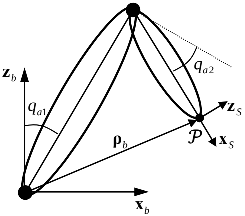
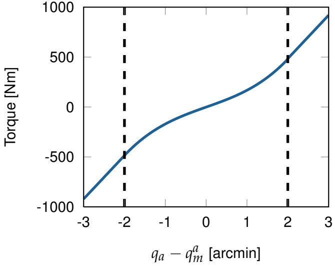
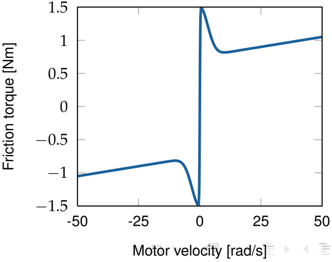
- Approximative filters have to be used for nonlinear models.
- In this work:
  - Extended Kalman filter (EKF) (Extended Kalman smoother (EKS))
    - Approximate the system with a linearisation of the nonlinear equations.
    - Assume additive Gaussian noise.
  - Particle filter (PF)
    - Approximate the posterior distribution with a large number of particles.
    - The optimal proposal distribution approximated using an EKF.

Robot model

- Serial robot with 2 DOF.
- Nonlinear stiffness.
- Nonlinear friction.

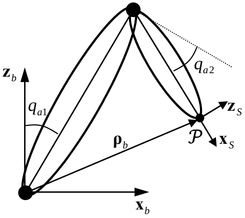






Accelerometer Model

- Acceleration from the motion.
- Acceleration due to the gravity.
- Rotation matrix from Ox_bz_b to Ox_sz_s.
- Bias parameter.



$$\ddot{\rho}_s(q_a) = \mathcal{R}_{b/s}(q_a)\left(\ddot{\rho}_b(q_a) + G_b\right) + \mathfrak{b}^{\text{ACC}}$$

1. Nonlinear estimation model

- State space vector:

$$x = \begin{pmatrix} x_1^\mathsf{T} & x_2^\mathsf{T} & x_3^\mathsf{T} & x_4^\mathsf{T} \end{pmatrix}^\mathsf{T} = \begin{pmatrix} q_a^\mathsf{T} & q_m^{a,\mathsf{T}} & \dot{q}_a^\mathsf{T} & \dot{q}_m^{a,\mathsf{T}} \end{pmatrix}^\mathsf{T}$$

- Physical model gives a continuous-time state space model.
- Discretisation using Euler sampling gives

$$x_{k+1} = f(x_k, u_k) + g(x_k)v_k.$$

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$$x_{k+1} = f(x_k, u_k) + g(x_k)v_k.$$

- Measurement equation:

$$y_k = \begin{pmatrix} x_{2,k} \\ \mathcal{R}_{b/s}(x_{1,k}) \left(J_{\mathrm{ACC}}(x_{1,k})\ddot{q}_{a,k} + \left(\frac{d}{dt} J_{\mathrm{ACC}}(x_{1,k}) \right) x_{3,k} + G_b \right) \end{pmatrix} + e_k$$

2. Estimation model with linear dynamic

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- Linear dynamic model (Double integrator in discrete time):

$$x_{k+1} = \mathcal{F} x_k + \mathcal{G}_u u_k + \mathcal{G}_v v_k$$

- The input signal is the jerk of the arm angle reference.

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- Measurement equation:

$$y_k = \begin{pmatrix} x_{1,k} + K^{-1} \left(M_a(x_{1,k}) x_{3,k} + C(x_{1,k}, x_{2,k}) + G(x_{1,k}) \right) \\ \mathcal{R}_{b/s}(x_{1,k}) \left(J_{\mathsf{ACC}}(x_{1,k}) x_{3,k} + \left(\frac{d}{dt} J_{\mathsf{ACC}}(x_{1,k}) \right) x_{2,k} + G_b \right) \end{pmatrix} + e_k$$

3. Nonlinear estimation model with acceleration as input

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- Arm angular acceleration calculated from the accelerometer signal.
- The physical model + Euler sampling give

$$x_{k+1} = \begin{pmatrix} x_{1,k} + T_s x_{3,k} \\ x_{2,k} + T_s x_{4,k} \\ x_{3,k} + T_s \ddot{q}_{a,k}^{\mathsf{IN}} \\ x_{4,k} + T_s M_m^{-1} \left(u_k - F(x_{4,k}) + T(x_{1,k} - x_{2,k}) + D(x_{3,k} - x_{4,k}) \right) \end{pmatrix} + g(x_k) v_k.$$

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4. Linear estimation model with acceleration as input

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- Arm angular acceleration calculated from the accelerometer signal.
- The physical model + Linear spring, damper and friction give

$$\dot{x} = \begin{pmatrix} \mathbf{0} & \mathbf{0} & \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ M_m^{-1}K & -M_m^{-1}K & M_m^{-1}D & -M_m^{-1}(D+F_d) \end{pmatrix} x + \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \\ \mathbf{I} & \mathbf{0} \\ \mathbf{0} & M_m^{-1} \end{pmatrix} \begin{pmatrix} \ddot{q}_a^{\mathsf{IN}} \\ u \end{pmatrix}.$$

- Discretisation using ZOH.

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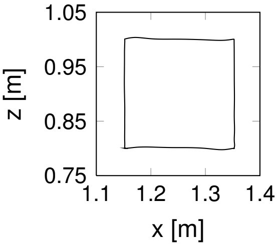
Experimental Setup

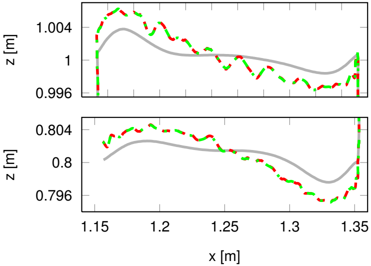
- Experiments performed on an ABB IRB4600.
- Only joints 2 and 3 are used.
- The true path is measured by a laser system from Leica.
- Synchronization errors and kinematic errors are present.

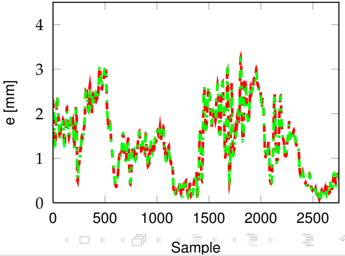


Calibration of the accelerometer: Patrik Axelsson and Mikael Norrlöf, **Method to Estimate the Position and Orientation of a Triaxial Accelerometer Mounted to an Industrial Manipulator**. In proceedings of the 10th International IFAC Symposium on Robot Control, 2012.

Results – EKF and EKS using Model 1

- Gives the same estimation.
- Higher orders of oscillation in the estimated paths.
- Bias states does not affect the result.
- The current MATLAB implementation not in real-time for the observers.



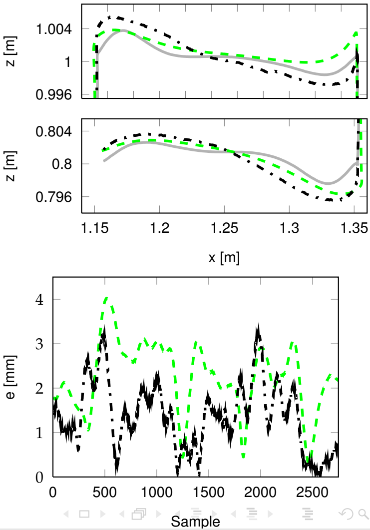


True path
EKF
EKS

Results – EKF and PF using Model 2

- Both filters follow the true path.
- The EKF passes in the corners.
- Bias states for both motor and accelerometer measurements are required to get good results.
- The current MATLAB implementation not in real-time for the observers.

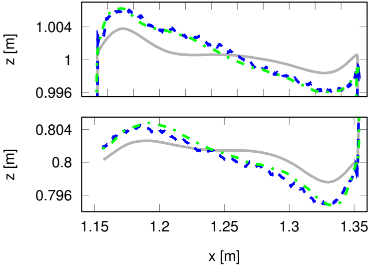
● True path
● EKF
● PF

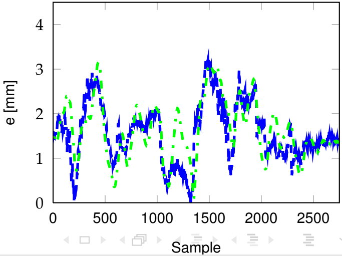


Results – EKF and Lin. obsv. using Model 3 and 4

- Linear model and pole placement works fine.
- Nonlinear model and EKF has higher orders of oscillations.
- No bias compensation.
- The current MATLAB implementation in real-time for the observers.

- True path
- EKF
- Lin. obs.





Experimental Results – Summary

- EKF + Model 1, PF + Model 2, and EKF + Model 3 are the best.
- Complexity: (Models and implementation)

  <u>EKF + Model 1</u> Much time spent on modelling.

  <u>PF + Model 2</u> Simpler modelling but more difficult to implement.

  <u>EKF + Model 3</u> Nonlinear joint model, no rigid body modelling.

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  PF + Model 2 Far from real-time.

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  EKF + Model 3 Real-time.
- Robustness:

  EKF + Model 3 No rigid body parameters.
- Other:

  PF + Model 2 Entire distribution of the states given. Used for e.g. control and diagnosis!?

AUTOMATIC CONTROL
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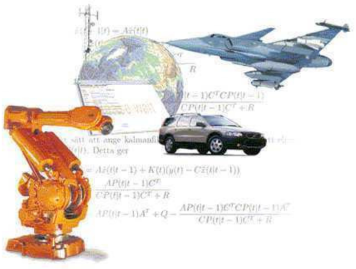

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