Extended Kalman Filter Applied to Industrial Manipulators

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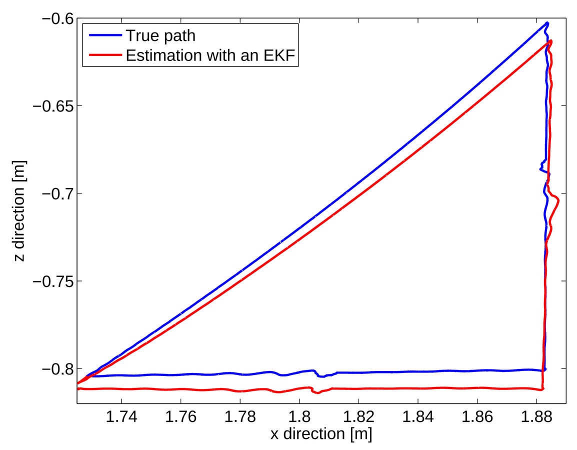
Background

The **problem** is to estimate the tool position for a flexible manipulator. The manipulator is a *resonant system* with *uncertainties* in the model parameters. There are also *high demands* on the accuracy of the estimation. Earlier work, see [1], has shown that the estimation is good for frequencies from 3 to 30 Hz but not so good for lower frequencies. The **aim** of this work is therefore to improve the estimation and include more degrees of freedom in the problem.



Models

A nonlinear two degrees of freedom **robot model** is used:

$$\dot{x} = f(x,u) = \begin{pmatrix} x_3 \\ x_4 \\ M^{-1}(x_1)(u - C(x) - G(x_1) - D(x) - \tau_s(x) - \kappa(x_4)) \end{pmatrix}$$

where $x_1 = q_a$, $x_2 = q_m$, $x_3 = \dot{q}_a$ and $x_4 = \dot{q}_m$. The measured acceleration in frame $\{s\}$ fixed to the sensor gives an **acceleration model**:

$$\ddot{\rho}_s^M = \ddot{\rho}_s + R_s^w(q_a)G_w + \delta_s + e_s.$$

$\ddot{\rho}_s$ is calculated as $R_s^w(q_a)\ddot{\rho}_w$. ρ_w is a vector from the origin of frame $\{w\}$ to the origin of frame $\{s\}$ expressed in frame $\{w\}$.

Notation

$M(q)$	Inertia matrix
$C(q,\dot{q})$	Coriolis- and centrifugal terms
$G(q)$	Gravitaion torque
$\tau_s(q)$	Nonlinear stiffness torque
$D(\dot{q})$	Damping torque
$\kappa(\dot{q})$	Nonlinear friction torque
$\ddot{\rho}_s$	Acceleration from the motion
$R_s^w(q_a)$	Rotation matrix from $\{w\}$ to $\{s\}$
G_w	Gravitation in $\{w\}$
δ_s	Drift
e_s	Measurement noise

Observer

An Extended Kalman Filter, *EKF*, is used to estimate the states of the robot. The forward kinematic is then used to get the tool position. Euler forward is used to discretize the state space model according to

$$x_{k+1} = F(x_k, u_k) + v_k, \quad F(x_k,u_k) = x_k + T_s f(x_k,u_k)$$

The measurements are motor angles and sensor acceleration and are expressed as

$$z_k = h(x_k,u_k) + w_k = \begin{pmatrix} x_{2k} \\ R_s^w(x_{1k})(\ddot{\rho}_w(x_k) + G_w) \end{pmatrix} + w_k.$$

Covariance Optimization

The problem is to choose the covariance matrices for the observer such that the path error is minimized. The path error is defined as

$$e_k = \min_i \sqrt{|p_{x,i} - \hat{p}_{x,k}|^2 + |p_{z,i} - \hat{p}_{z,k}|^2},$$

where $p_{x,i}$, $\hat{p}_{x,k}$, $p_{z,i}$ and $\hat{p}_{z,k}$ are the true and estimated position for the tool in the x- and z-direction at time k and time i, respectively.

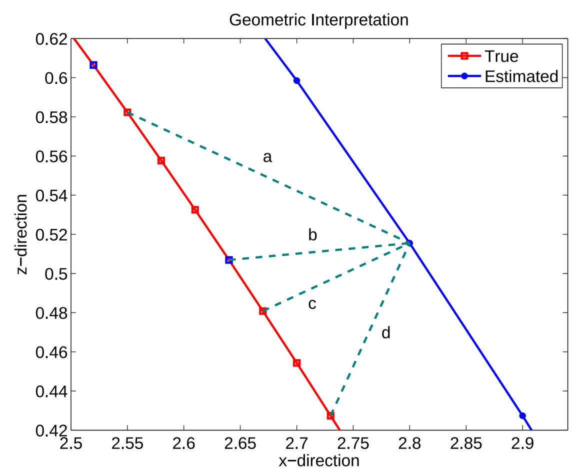
$$\text{Minimize } f_{obj}(\hat{p}_x, \hat{p}_z) = \sqrt{\textstyle\sum_{k=1}^N |e_k|^2}$$

$$\text{subject to } \lambda_j > 0 \quad j = 1,\ldots,5$$

$$\tilde{Q}_\lambda = \begin{pmatrix} \lambda_1 I_{2\times2} & 0 & 0 & 0 \\ 0 & \lambda_2 I_{2\times2} & 0 & 0 \\ 0 & 0 & \lambda_3 I_{2\times2} & 0 \\ 0 & 0 & 0 & \lambda_4 I_{2\times2} \end{pmatrix} \tilde{Q}$$

$$\tilde{R}_\lambda = \begin{pmatrix} \lambda_5 I_{2\times2} & 0 \\ 0 & I_{2\times2} \end{pmatrix} \tilde{R}$$

$$(\hat{p}_x, \hat{p}_z) = \text{EKF}(\tilde{Q}_\lambda, \tilde{R}_\lambda)$$



λ_j – Optimization parameters
$\tilde{Q}$ & $\tilde{R}$ – Diagonal matrices with elements taken from an initial guess of the covariances of v and w.

Simulation Setup

Three types of simulations are executed on 4 different paths. A set of covariance matrices are then optimized for each simulation.

Sim1: Without errors

Sim2: With calibration errors, drift and model errors

Sim3: With calibration errors, drift and without model errors

Cov1: Optimized for Sim1 on Path A (Red)

Cov2: Optimized for Sim2 on Path A (Green)

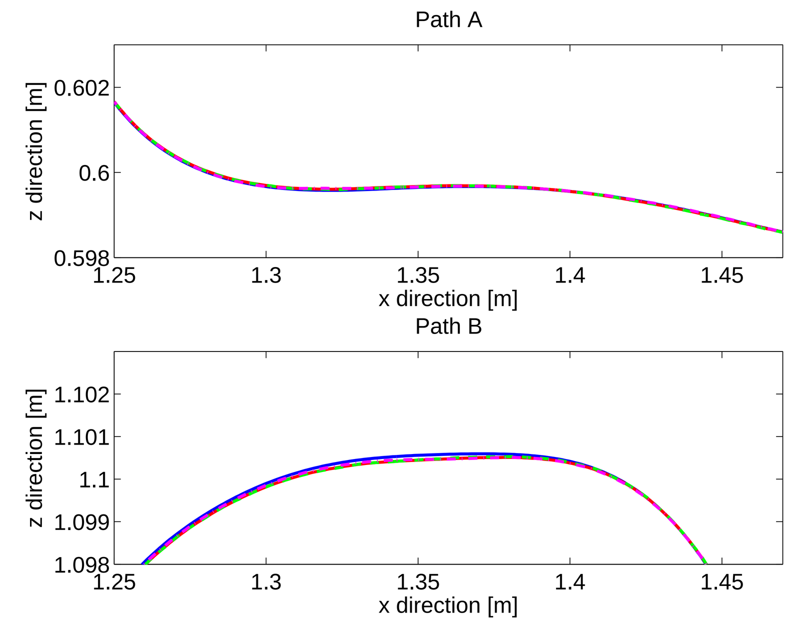
Cov3: Optimized for Sim3 on Path A (Magenta)

Result

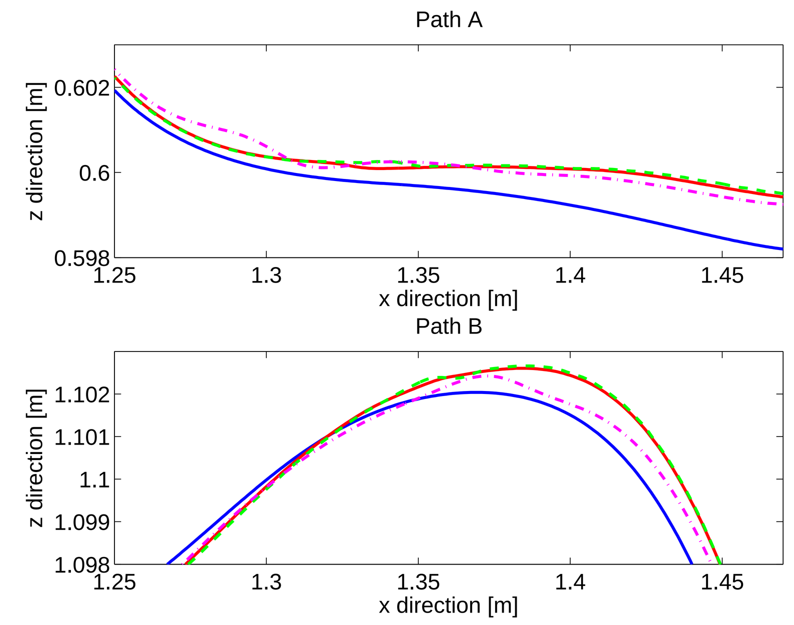
All 9 combinations of the simulations and the covariance matrices are used to evaluate the performance of the observer.

- No global optimum obtained for the covariance optimization.
- Difficult to get good estimations when model errors are present.
- Calibration errors and offsets for the accelerometer do not affect very much.
- The covariance matrices may be dependent of the states.

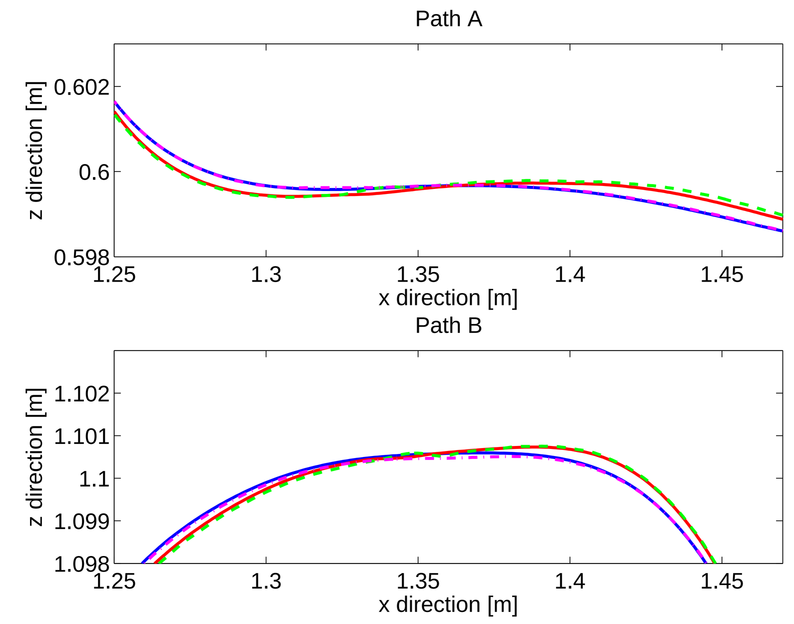
Estimation on Sim1 for three different covariance matrices



Estimation on Sim2 for three different covariance matrices



Estimation on Sim3 for three different covariance matrices



Max and mean error in mm for the EKF on path A

Path A	COV1		COV2		COV3	
	MAX	MEAN	MAX	MEAN	MAX	MEAN
SIM1	0.078	0.025	0.080	0.025	0.080	0.026
SIM2	1.681	0.550	1.577	0.543	1.910	0.661
SIM3	0.400	0.113	0.903	0.172	0.079	0.027

Max and mean error in mm for the EKF on path B

Path B	COV1		COV2		COV3	
	MAX	MEAN	MAX	MEAN	MAX	MEAN
SIM1	0.124	0.035	0.126	0.035	0.112	0.035
SIM2	1.908	0.654	1.966	0.657	2.137	0.687
SIM3	0.419	0.082	0.842	0.120	0.111	0.035

Conclusions and Future Work

- The offset in the estimation in [1] is not present in simulations.
- Use paths that better cover the complete robot workspace to see if the covariance matrices are dependent of the states.
- The optimization of the covariance matrices is a challenge for future work.
- Investigate the noise model for the process noise. Is it sufficient with additive noise?
- Examine if Euler forward affect the discretization of the continuous state space model.
- Perform a structuralized sensitivity analysis w.r.t. stiffness, friction and calibration parameters.
- New experimental data for validation.

Acknowledgement

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[1] R. Henriksson, M. Norrlöf, S. Moberg, E. Wernholt and T. Schön, *Experimental Comparison of Observers for Tool Position Estimation of Industrial Robots*, 2009, to appear in the 48th IEEE Conference on Decision and Control.