The Iterative extended Kalman filter

Sensor fusion & nonlinear filtering

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ITERATED EXTENDED KALMAN FILTERS

The Iterated EKF (IEKF)

- Once we have computed $\hat{\mathbf{x}}_{k|k}$ we have a better guess about $\mathbf{x}_k$

  $\rightsquigarrow$ we can linearize $\mathbf{h}(\mathbf{x}_k)$ around that point and update $p(\mathbf{x}_k | \mathbf{y}_{1:k-1})$ using the new linearization and $\mathbf{y}_k$.

- **Note:**
  - we obtain an iterative algorithm that we can run until convergence,
  - each update starts with the predicted density $\mathcal{N}(\mathbf{x}_k; \hat{\mathbf{x}}_{k|k-1}, \mathbf{P}_{k|k-1})$ to avoid using $\mathbf{y}_k$ multiple times.

IEKF: REMARKS

IEKF – Gauss Newton search

- One can show that the IEKF solves

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k}^{\mathbf{MAP}} = \arg\max_{\mathbf{x}_k} p(\mathbf{x}_k \big| \mathbf{y}_{1:k})$$

  iteratively using a Gauss-Newton search.

EKF: THE UPDATE STEP

EKF update step – Example 2

- Prediction:

$$x_k | y_{1:k-1} \sim \mathcal{N}(3, 3.5^2)$$

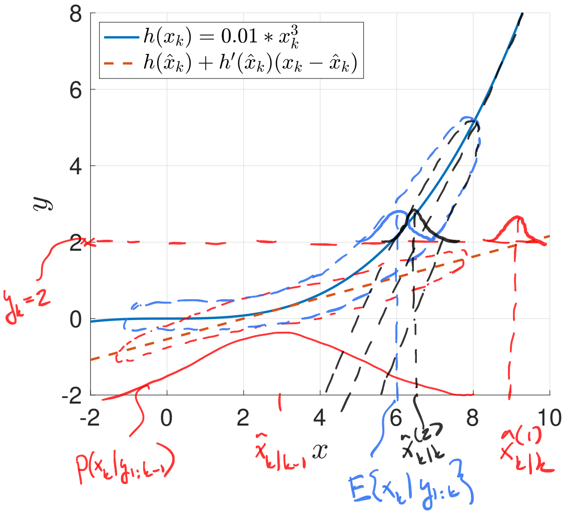
- Measurement: $y_k = 2$

$$y_k = h(x_k) + r_k$$

$$h(x_k) = 0.01 x_k^3$$

$$r_k \sim \mathcal{N}(0, 0.3)$$

- Find the posterior mean $\mathbb{E}\{x_k | y_{1:k}\}$ and the approximate posterior mean $\hat{x}_{k|k}$ given by EKF.



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Pros:

- the IEKF usually performs very well when the measurement noise is small (the MAP estimate is accurate then).
- the IEKF often converges in very few iterations.

Cons:

- posterior pdfs are often rather skewed
  $\Rightarrow$ the MAP estimate is far from the posterior mean.
- the IEKF may diverge (more robust alternatives exist).