

EE 565: Position, Navigation, and Timing

Kalman Filtering Example

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$$\dot{\vec{x}}(t) = F(t)\vec{x}(t) + G(t)\vec{w}(t) \quad (1)$$

$$\vec{y}(t) = H(t)\vec{x}(t) + \vec{v}(t) \quad (2)$$

System Discretization

$$\Phi_{k-1} = e^{F_{k-1}\tau_s} \approx \mathcal{I} + F_{k-1}\tau_s \quad (3)$$

where F_{k-1} is the average of F at times t and $t - \tau_s$, and first order approximation is used. Leading to

$$\vec{x}_k = \Phi_{k-1} \vec{x}_{k-1} + \vec{w}_{k-1} \quad (4)$$

$$\vec{z}_k = H_k \vec{x}_k + \vec{v}_k \quad (5)$$

- \vec{w}_k and \vec{v}_k are drawn from a Gaussian distribution, uncorrelated have zero mean and statistically independent.

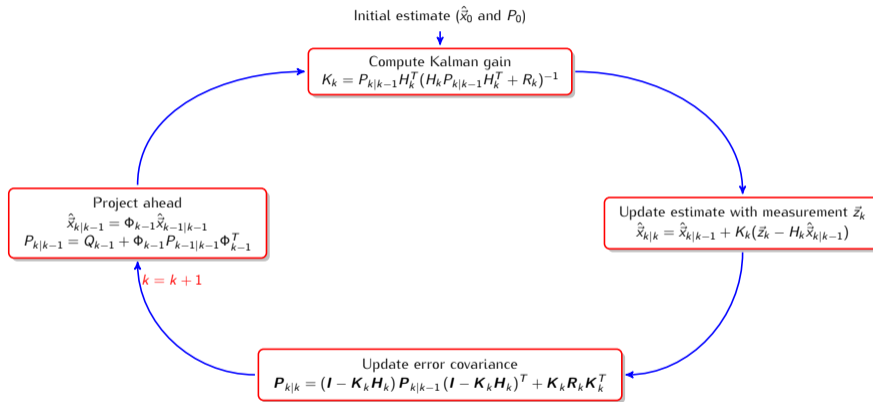
$$\mathbb{E}\{\vec{w}_k \vec{w}_i^T\} = \begin{cases} Q_k & i = k \\ 0 & i \neq k \end{cases} \quad (6)$$

$$\mathbb{E}\{\vec{v}_k \vec{v}_i^T\} = \begin{cases} R_k & i = k \\ 0 & i \neq k \end{cases} \quad (7)$$

$$\mathbb{E}\{\vec{w}_k \vec{v}_i^T\} = \begin{cases} 0 & \forall i, k \end{cases} \quad (8)$$

- State covariance matrix

$$Q_{k-1} \approx \frac{1}{2} \left[\Phi_{k-1} G_{k-1} Q(t_{k-1}) G_{k-1}^T \Phi_{k-1}^T + G_{k-1} Q(t_{k-1}) G_{k-1}^T \right] \tau_s \quad (9)$$



- Kalman filter (KF) is optimal under the assumptions that the system is linear and the noise is uncorrelated
- Under these assumptions KF provides an unbiased and minimum variance estimate.
- If the Gaussian assumptions is not true, Kalman filter is biased and not minimum variance.
- If the noise is correlated we can augment the states of the system to maintain the uncorrelated requirement of the system noise.

Given a state space system

$$\dot{\vec{x}}_1(t) = F_1(t)\vec{x}_1(t) + G_1(t)\vec{w}_1(t)$$

$$\vec{y}_1(t) = H_1(t)\vec{x}_1(t) + \vec{v}_1(t)$$

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As we have seen the noise $\vec{w}_1(t)$ may be non-white, e.g., correlated Gaussian noise, and as such may be modeled as

$$\dot{\vec{x}}_2(t) = F_2(t)\vec{x}_2(t) + G_2(t)\vec{w}_2(t)$$

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$$\vec{w}_1(t) = H_2(t)\vec{x}_2(t)$$

Define a new augmented state

$$\vec{x}_{aug} = \begin{pmatrix} \vec{x}_1(t) \\ \vec{x}_2(t) \end{pmatrix} \quad (10)$$

therefore,

$$\dot{\vec{x}}_{aug} = \begin{pmatrix} \dot{\vec{x}}_1(t) \\ \dot{\vec{x}}_2(t) \end{pmatrix} = \begin{pmatrix} F_1(t) & G_1 H_2(t) \\ 0 & F_2(t) \end{pmatrix} \begin{pmatrix} \vec{x}_1(t) \\ \vec{x}_2(t) \end{pmatrix} + \begin{pmatrix} 0 \\ G_2(t) \end{pmatrix} \vec{w}_2(t) \quad (11)$$

and

$$\vec{y}(t) = \begin{pmatrix} H_1(t) & 0 \end{pmatrix} \begin{pmatrix} \vec{x}_1(t) \\ \vec{x}_2(t) \end{pmatrix} + \vec{v}_1(t) \quad (12)$$

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In this case the measurement noise \vec{v}_1 may be correlated

$$\dot{\vec{x}}_2(t) = F_2(t)\vec{x}_2(t) + G_2(t)\vec{v}_2(t)$$

$$\vec{v}_1(t) = H_2(t)\vec{x}_2(t)$$

Define a new augmented state

$$\vec{x}_{aug} = \begin{pmatrix} \vec{x}_1(t) \\ \vec{x}_2(t) \end{pmatrix} \quad (13)$$

therefore,

$$\dot{\vec{x}}_{aug} = \begin{pmatrix} \dot{\vec{x}}_1(t) \\ \dot{\vec{x}}_2(t) \end{pmatrix} = \begin{pmatrix} F_1(t) & 0 \\ 0 & F_2(t) \end{pmatrix} \begin{pmatrix} \vec{x}_1(t) \\ \vec{x}_2(t) \end{pmatrix} + \begin{pmatrix} G_1(t) & 0 \\ 0 & G_2(t) \end{pmatrix} \begin{pmatrix} \vec{w}(t) \\ \vec{v}_2(t) \end{pmatrix} \quad (14)$$

and

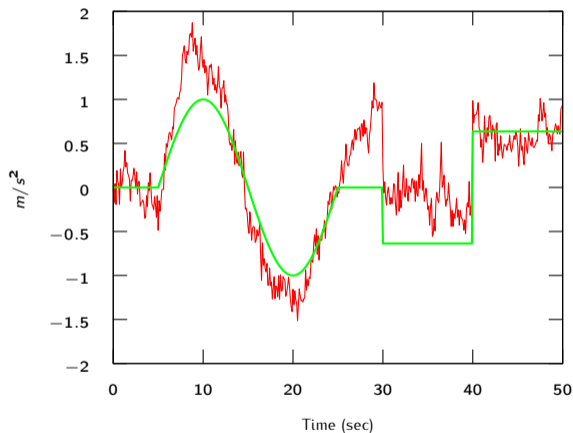
$$\vec{y}(t) = \begin{pmatrix} H_1(t) & H_2(t) \end{pmatrix} \begin{pmatrix} \vec{x}_1(t) \\ \vec{x}_2(t) \end{pmatrix} \quad (15)$$

You are to design a system that estimates the position and velocity of a moving point in a straight line. You have:

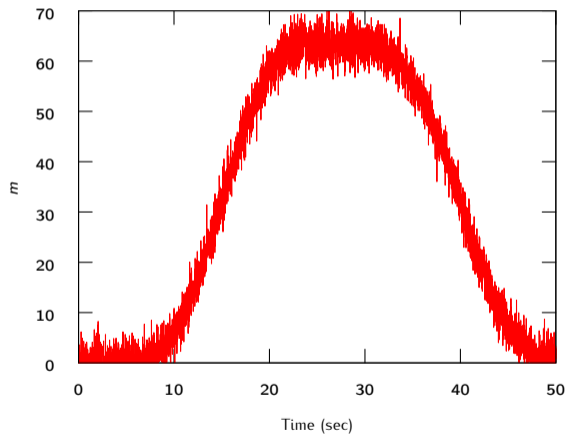
- 1 an accelerometer corrupted with noise
- 2 an aiding sensor allowing you to measure absolute position that is also corrupted with noise.

- Sampling Rate $F_s = 100\text{Hz}$.
- Accelerometer specs
 - 1 VRW = $1\text{mg}/\sqrt{\text{Hz}}$.
 - 2 BI = 7mg with correlation time 6s.
- Position measurement is corrupted with WGN. $\sim \mathcal{N}(0, \sigma_p^2)$, where $\sigma_p = 2.5\text{m}$

True Acceleration and Acceleration with Noise

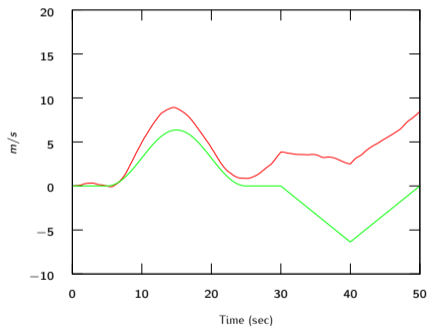
Meas Accel 

Absolute position measurement corrupted with noise



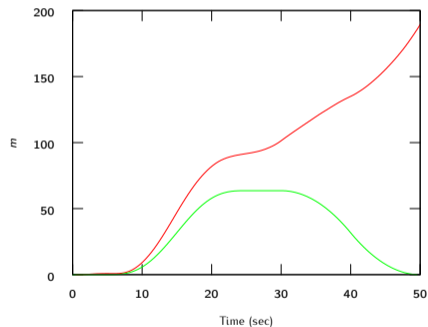
Using only the acceleration measurement and an integration approach to compute the velocity, then integrate again to get position.

Velocity



Directly Computed Vel ———
True Vel ———

Position



Directly Computed Pos ———
True Pos ———

- 1 Clean up the noisy input to the system by filtering
- 2 Use Kalman filtering techniques with

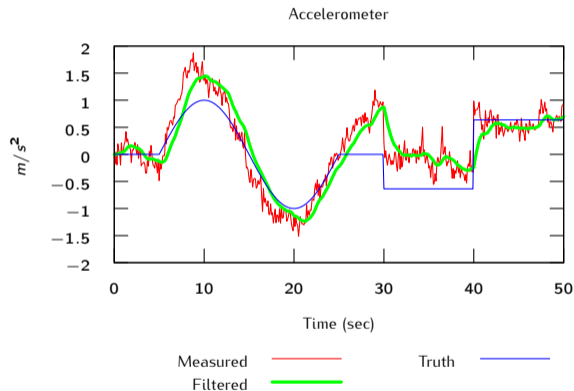
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 - A model of the system dynamics (too restrictive)
 - A model of the error dynamics and correct the system output in
 - open-loop configuration, or
 - closed-loop configuration.

Approach 1 — Filtered input

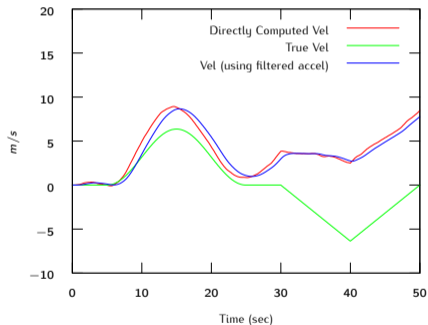
Filtered Accel Measurement



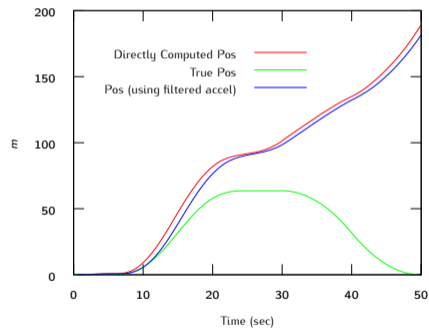
Approach 1 — Filtered input

Position and Velocity

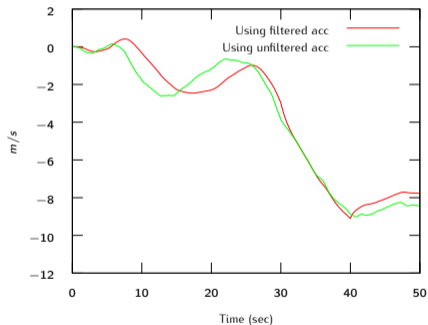
Velocity



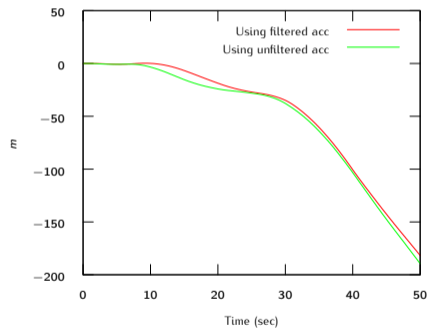
Position

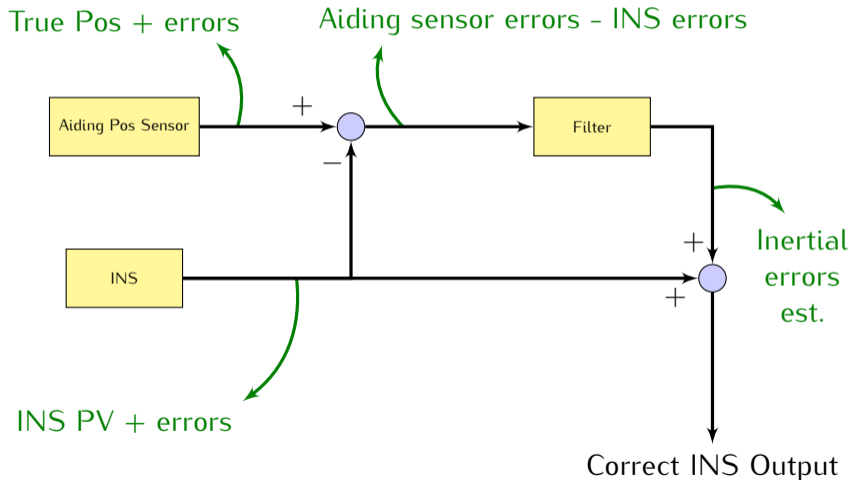


Velocity Error

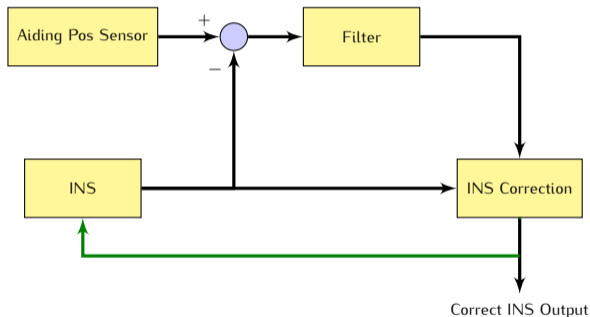


Position Error





If error estimates are fed back to correct the INS mechanization, a reset of the state estimates becomes necessary.



- State noise covariance matrix (continuous)

$$\mathbb{E}\{\vec{w}(t)\vec{w}^T(\tau)\} = Q(t)\delta(t - \tau)$$

- State noise covariance matrix (discrete)

$$\mathbb{E}\{\vec{w}_k\vec{w}_i^T\} = \begin{cases} Q_k & i = k \\ 0 & i \neq k \end{cases}$$

- Measurement noise covariance matrix

$$\mathbb{E}\{\vec{v}_k\vec{v}_i^T\} = \begin{cases} R_k & i = k \\ 0 & i \neq k \end{cases}$$

- Initial error covariance matrix

$$P_0 = \mathbb{E}\{(\vec{x}_0 - \hat{\vec{x}}_0)(\vec{x}_0 - \hat{\vec{x}}_0)^T\} = \mathbb{E}\{\vec{e}_0\vec{e}_0^T\}$$

The position, velocity and acceleration may be modeled using the following kinematic model.

$$\begin{aligned}\dot{p}(t) &= v(t) \\ \dot{v}(t) &= a(t)\end{aligned}\tag{16}$$

where $a(t)$ is the input. Therefore, our estimate of the position is $\hat{p}(t)$ that is the double integration of the acceleration.

Assuming that the accelerometer sensor measurement may be modeled as

$$\tilde{a}(t) = a(t) + b(t) + w_a(t) \quad (17)$$

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and the bias is Markov, therefore

$$\dot{b}(t) = -\frac{1}{T_c} b(t) + w_b(t) \quad (18)$$

where $w_a(t)$ and $w_b(t)$ are zero mean WGN with variances, respectively, $F_s \cdot VRW^2$

$$\mathbb{E}\{w_b(t)w_b(t + \tau)\} = Q_b(t)\delta(t - \tau) \quad (19)$$

$$Q_b(t) = \frac{2\sigma_{BI}^2}{T_c} \quad (20)$$

and T_c is the correlation time and σ_{BI} is the bias instability.

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Make sure that the VRW and σ_{BI} are converted to have SI units.

Define error terms as

$$\delta p(t) = p(t) - \hat{p}(t), \quad (21)$$

$$\begin{aligned} \delta \dot{p}(t) &= \dot{p}(t) - \dot{\hat{p}}(t) \\ &= v(t) - \hat{v}(t) \\ &= \delta v(t) \end{aligned} \quad (22)$$

and

$$\begin{aligned} \delta \dot{v}(t) &= \dot{v}(t) - \dot{\hat{v}}(t) \\ &= a(t) - \hat{a}(t) \\ &= -b(t) - w_a(t) \end{aligned} \quad (23)$$

where $b(t)$ is modeled as shown in Eq. 18

$$\begin{aligned}\dot{\vec{x}}(t) &= \begin{pmatrix} \delta \dot{p}(t) \\ \delta \dot{v}(t) \\ \dot{b}(t) \end{pmatrix} = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & -1 \\ 0 & 0 & -\frac{1}{T_c} \end{pmatrix} \begin{pmatrix} \delta p(t) \\ \delta v(t) \\ b(t) \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ w_a(t) \\ w_b(t) \end{pmatrix} \\ &= F(t)\vec{x}(t) + G(t)\vec{w}(t)\end{aligned}\quad (24)$$

- The continuous state noise covariance matrix $Q(t)$ is

$$Q(t) = \begin{pmatrix} 0 & 0 & 0 \\ 0 & VRW^2 & 0 \\ 0 & 0 & \frac{2\sigma_{Bl}^2}{T_c} \end{pmatrix} \quad (25)$$

- The measurement noise covariance matrix is $R = \sigma_p^2$, where σ_p is the standard deviation of the noise of the absolute position sensor.

Now we are ready to start the implementation but first we have to discretize the system.

$$\vec{x}(k+1) = \Phi(k)\vec{x}(k) + \vec{w}_d(k) \quad (26)$$

where

$$\Phi(k) \approx \mathcal{I} + Fdt \quad (27)$$

with the measurement equation

$$y(k) = H\vec{x} + w_p(k) = \delta p(k) + w_p(k) \quad (28)$$

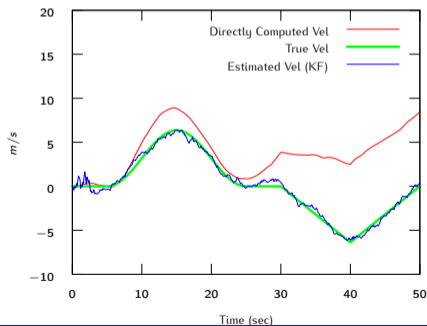
where $H = [1 \ 0 \ 0]$. The discrete Q_d is approximated as

$$Q_{k-1} \approx \frac{1}{2} [\Phi_{k-1} G(t_{k-1}) Q(t_{k-1}) G^T(t_{k-1}) \Phi_{k-1}^T + G(t_{k-1}) Q(t_{k-1}) G^T(t_{k-1})] dt \quad (29)$$

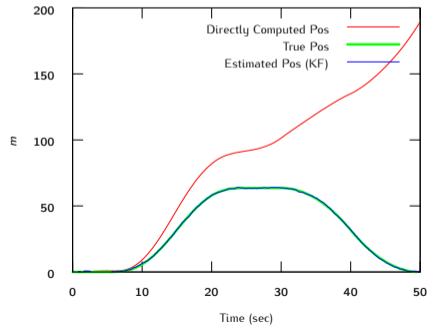
Open-loop Correction

Best estimate = INS out (pos & vel) + KF est error (pos & vel)

Velocity



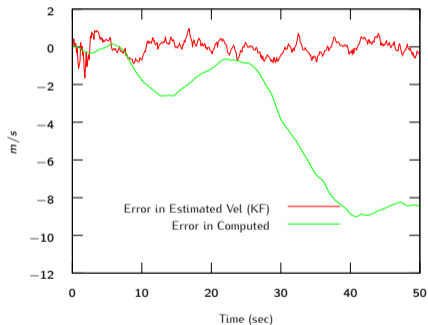
Position



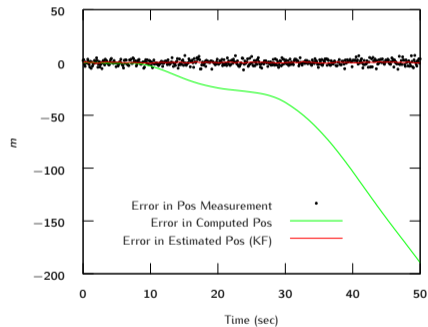
Approach 2 — Open-Loop Compensation

Position and Velocity Errors

Velocity Error



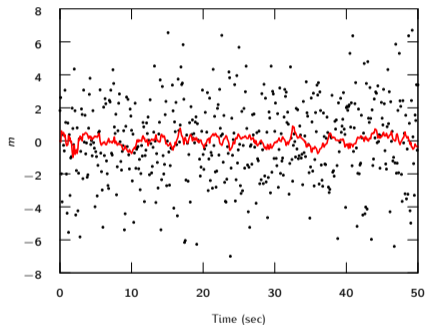
Position Error



Approach 2 — Open-Loop Compensation

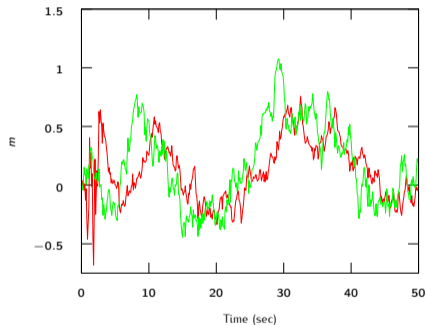
Pos Error & Bias Estimate

Position Error



Error in Pos Measurement •
Error in Estimated Pos (KF) —

Bias



Est. Bias —
True Bias —

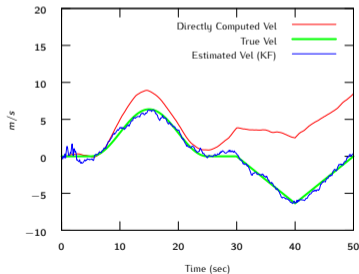
Closed-loop Correction

Best estimate = INS out (pos,vel, & bias) + KF est error (pos, vel & bias)

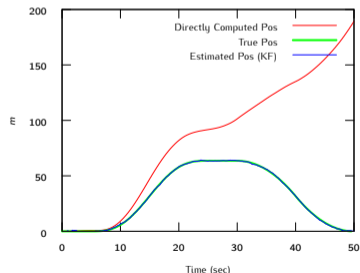
Use best estimate on next iteration of INS

Accel estimate = accel meas - est bias

Reset state estimates before next call to KF



Velocity

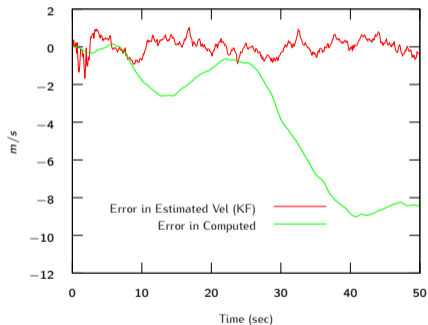


Position

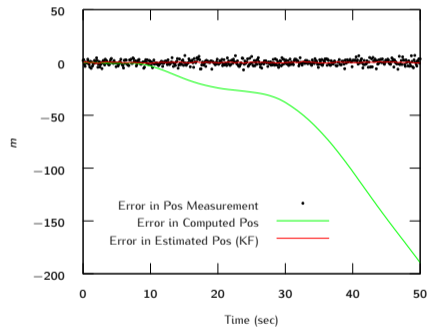
Approach 3 — Closed-Loop Compensation

Position and Velocity Errors

Velocity Error



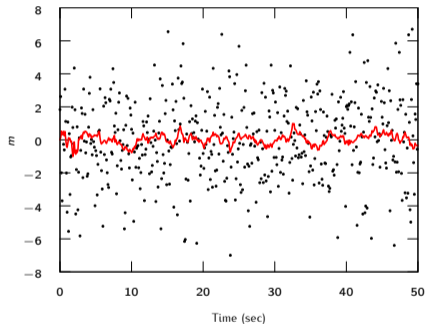
Position Error



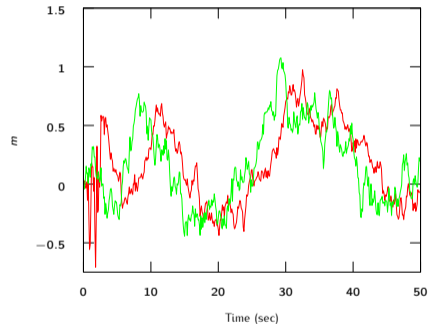
Approach 3 — Closed-Loop Compensation

Pos Error & Bias Estimate

Position Error



Error in Pos Measurement •
Error in Estimated Pos (KF) —



Est. Bias —
True Bias —

Bias