Real-world issue: Initialization

- If battery load is “off” for a “long” time, just assume that cell voltage is equivalent to OCV:
  - Reset SOC estimate based on OCV
  - Set diffusion voltages to zero
  - Keep prior value of hysteresis state
- If load has been off for a “short” period of time
  - Set up and execute simple time/measurement update (simple KF) equations for SOC and diffusion voltages
  - Hysteresis voltages do not change
  - Run a single-step Kalman filter to update state estimate based on total time off

Real-world issue: Tuning $\Sigma_{\tilde{x},0}$

- KF “tuning” accomplished via changing $\Sigma_{\tilde{x},0}$, $\Sigma_{\widetilde{w}}$, $\Sigma_{\tilde{v}}$
- Ideally, $\Sigma_{\tilde{x},0} = \mathbb{E}[(x_0 - \hat{x}_0^+)(x_0 - \hat{x}_0^+)^T]$
- Since we don’t know x_0 exactly, not possible to initialize $\hat{x}_0^+$ to exactly correct value: Uncertainty in $\hat{x}_0^+$ captured by $\Sigma_{\tilde{x},0}$
- If we assume model states uncorrelated, $\Sigma_{\tilde{x},0}$ is diagonal
  - We often make this assumption simply because we have no better information regarding state correlation
  - Diagonal elements in $\Sigma_{\tilde{x},0}$ are variances of initial estimation errors of the corresponding state elements in x
- Set diagonal elements of $\Sigma_{\tilde{x},0}$ such that you expect true state to lie between $\hat{x}_0^+ \pm 3\sqrt{\text{diag}(\Sigma_{\tilde{x},0})}$

Real-world issue: Tuning $\Sigma_{\widetilde{w}}$

- Assuming model of cell is perfect, $\Sigma_{\widetilde{w}}$ is covariance matrix of “process noise” w_k driving cell

$$x_{k+1} = Ax_k + Bu_k + w_k$$

- Process noise is any unmeasured (zero-mean, white) input that affects state vector
- If w_k chosen to model current-sensor noise, then $\Sigma_{\widetilde{w}}$ can be determined statistically via experimentation
- But, as no model is perfect, $\Sigma_{\widetilde{w}}$ also attempts to capture—in some way—state-equation inaccuracies, so should have larger uncertainty than simply representing current-sensor noise alone

Real-world issue: Tuning $\Sigma_{\tilde{v}}$

- Assuming model of cell is perfect, $\Sigma_{\tilde{v}}$ is the covariance matrix of "measurement noise" v_k

$$y_k = Cx_k + Du_k + v_k$$

- Measurement noise is any unmeasured (zero-mean, white) input that doesn't affect state vector, but which does corrupt measurements
- If v_k chosen to model voltage-sensor noise, then $\Sigma_{\tilde{v}}$ can be determined statistically via experimentation (or data sheet)
- But, as no model is perfect, $\Sigma_{\tilde{v}}$ also attempts to capture—in some way—output-equation inaccuracies, so should have larger uncertainty than simply representing voltage-sensor noise alone

Rate of convergence

- Filter convergence rates are determined by $\Sigma_{\tilde{w}}$ and $\Sigma_{\tilde{v}}$
  - Large $\Sigma_{\tilde{w}}$ says "trust sensor more than model" and makes state error bounds large
  - Large $\Sigma_{\tilde{v}}$ says "trust model more than sensor" and converges slowly (pseudo open loop)
- Since model inaccuracies are difficult to quantify, some trial-and-error "tuning" of $\Sigma_{\tilde{w}}$ and $\Sigma_{\tilde{v}}$ is common
- In some cases (noisy sensors or bad model), desired state-estimate accuracy and convergence rates are simply impossible
- In general, it is not possible to have arbitrarily fast convergence to arbitrarily narrow error bounds

Summary

- You have learned how to set $\Sigma_{\tilde{x},0}$ during initialization
- You have seen tips on tuning $\Sigma_{\tilde{w}}$, which represents process-noise (e.g., current-sensor noise and inaccuracies in state equation) uncertainty
- You have seen some tips on tuning $\Sigma_{\tilde{v}}$, which represents sensor-noise (e.g., voltage-sensor noise and inaccuracies in voltage equation) uncertainty
- Since model inaccuracies are difficult to quantify, some trial-and-error "tuning" of $\Sigma_{\tilde{w}}$ and $\Sigma_{\tilde{v}}$ is common
- Since convergence rates depend on $\Sigma_{\tilde{w}}$ and $\Sigma_{\tilde{v}}$, it is not possible in general to have arbitrarily fast convergence to arbitrarily narrow error bounds
- Still, KF is optimal MMSE estimator for the assumptions made during derivation

Credits

Credits for photos in this lesson

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