

Day 21

Kalman Filter Examples

# Static State Estimation

- ▶ recall the static state estimation problem we have been studying
  - ▶ the process or plant model

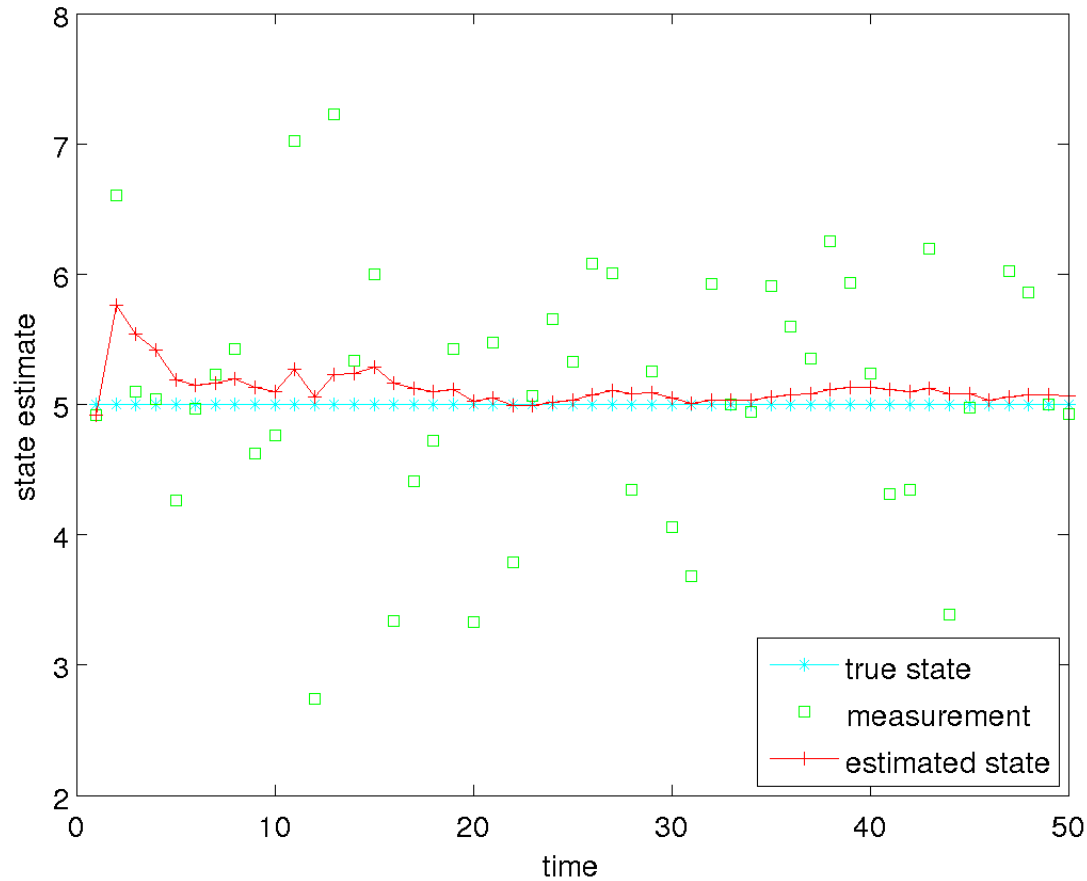
$$A_t = 1, \quad B_t = 0, \quad R_t = 0 \quad x_t = A_t x_{t-1} + B_t u_t + \varepsilon_t \\ = x_{t-1}$$

- ▶ the observation model

$$C_t = 1, \quad Q_t = \sigma_t^2 \quad z_t = x_t + \delta_t$$

# Static State Estimation

- ▶ how well does the Kalman filter work

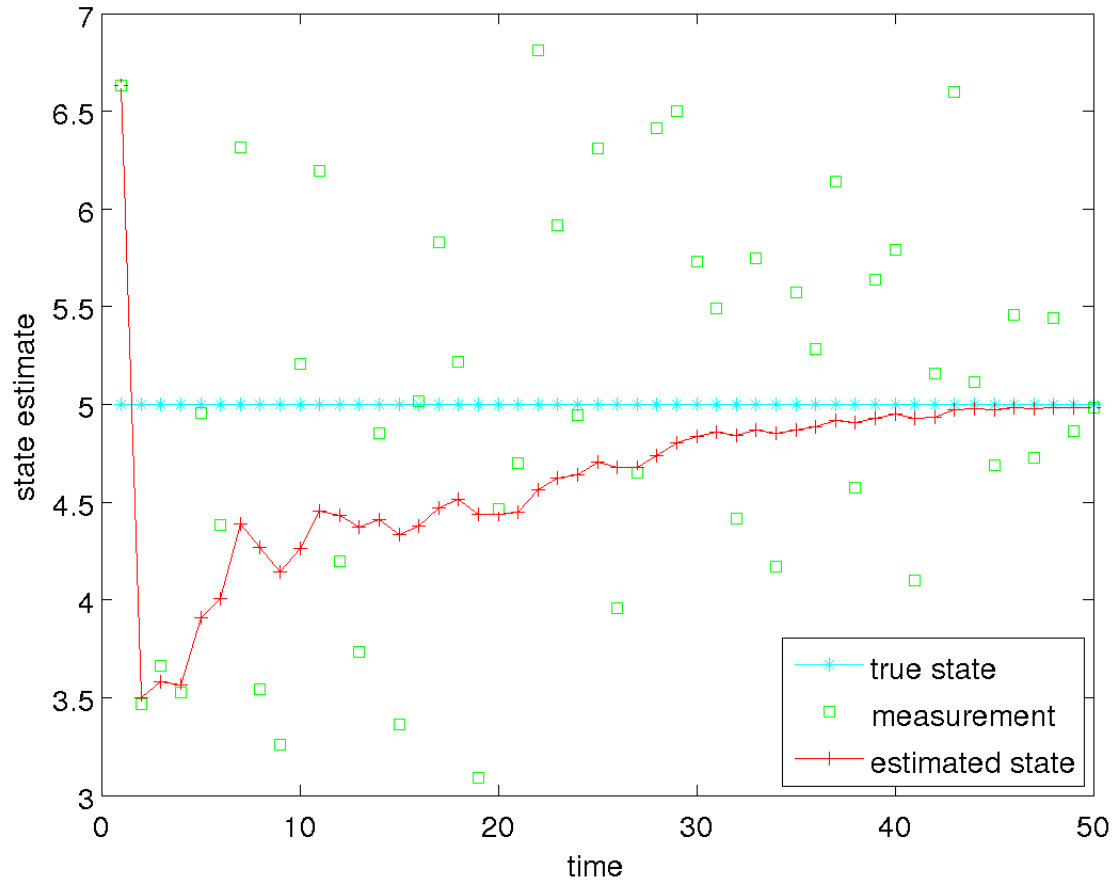


# Static State Estimation

- ▶ notice that we need to specify the measurement noise covariance  $Q_t$
- ▶ how sensitive is the Kalman filter to  $Q_t$  ?
  - ▶ e.g., what if we use a  $Q_t$  that is much smaller than the actual measurement noise?
  - ▶ e.g., what if we use a  $Q_t$  that is much larger than the actual measurement noise?

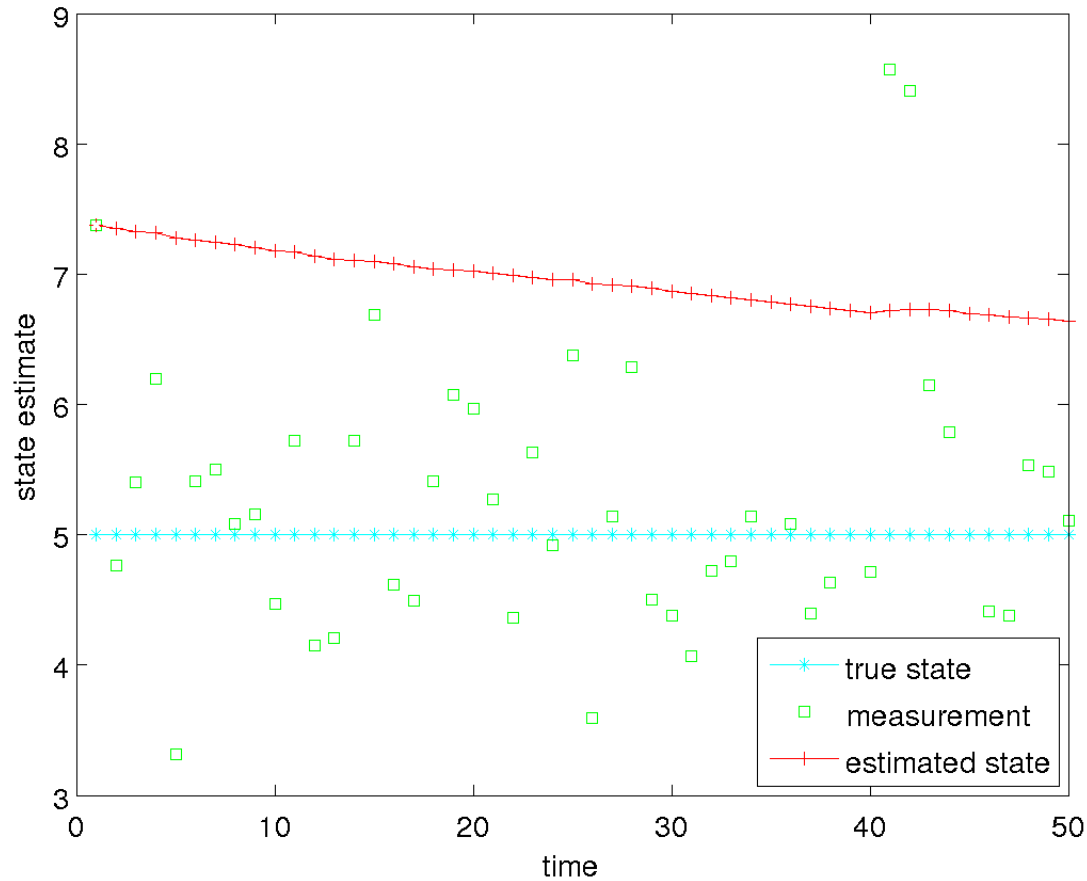
# Static State Estimation

- ▶ specified  $Q_t = 0.01$  \* actual  $Q_t$



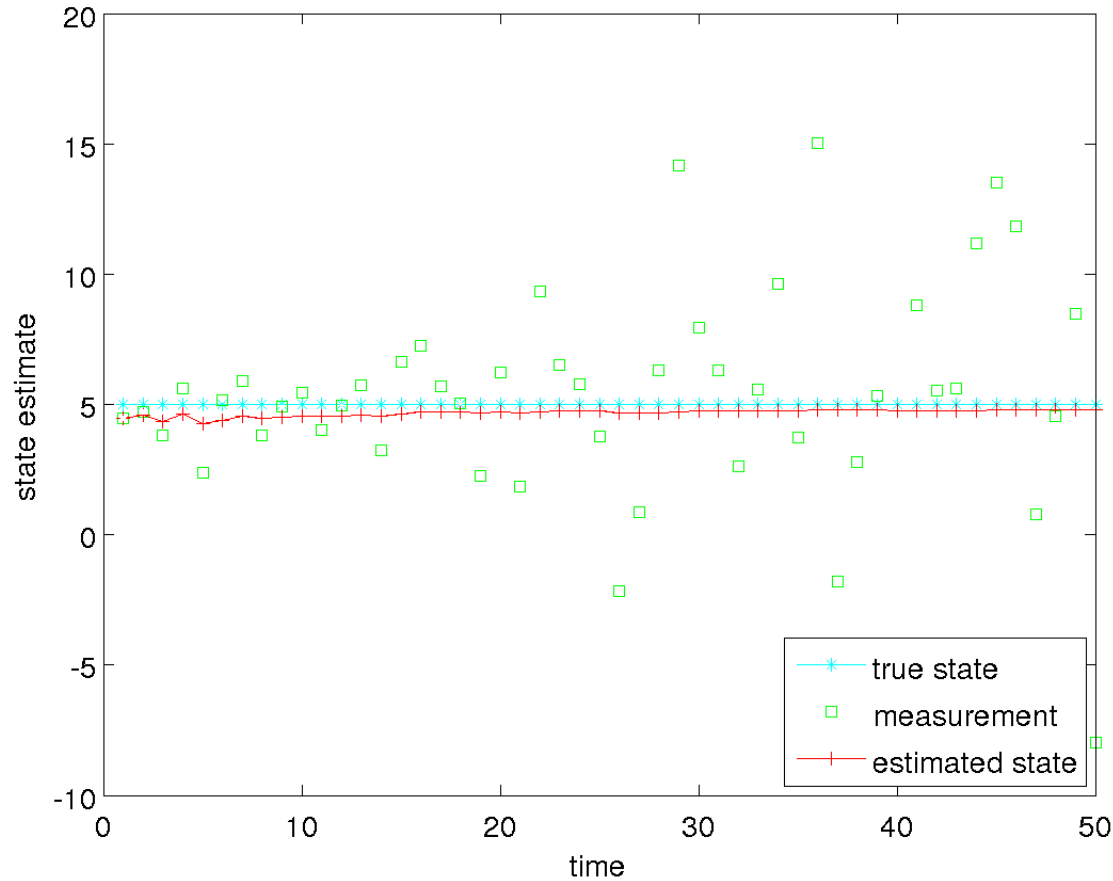
# Static State Estimation

- ▶ specified  $Q_t = 100 * \text{actual } Q_t$



# Static State Estimation

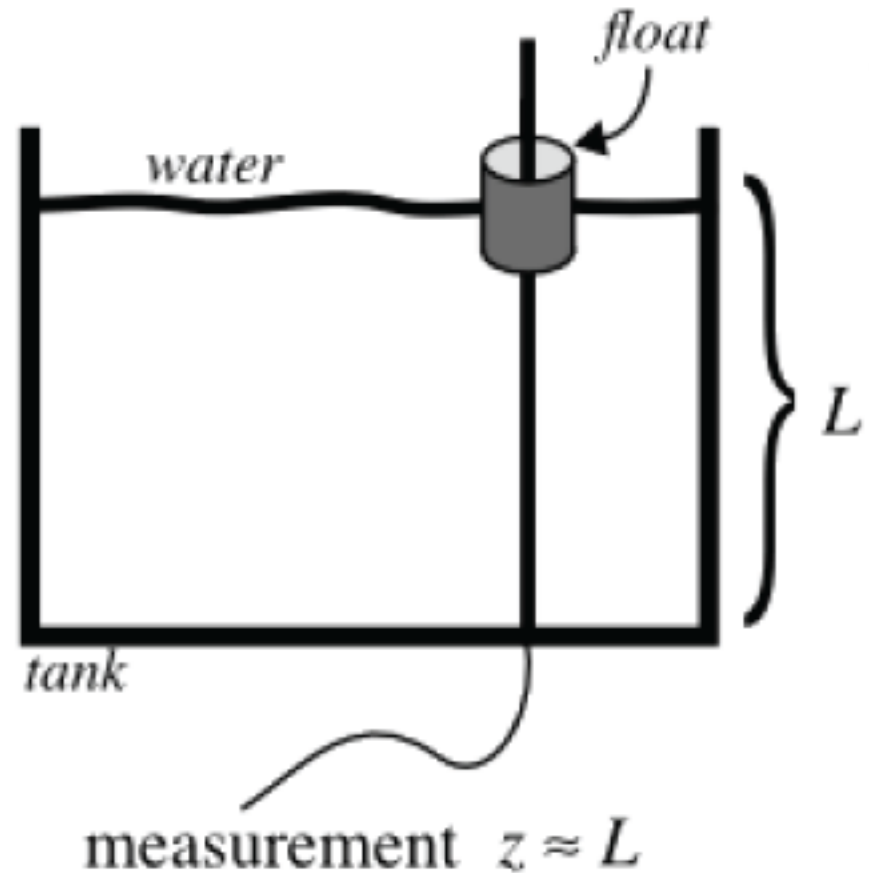
- ▶ suppose our measurements get progressively noisier over time



noise variance increases 10% for each successive measurement

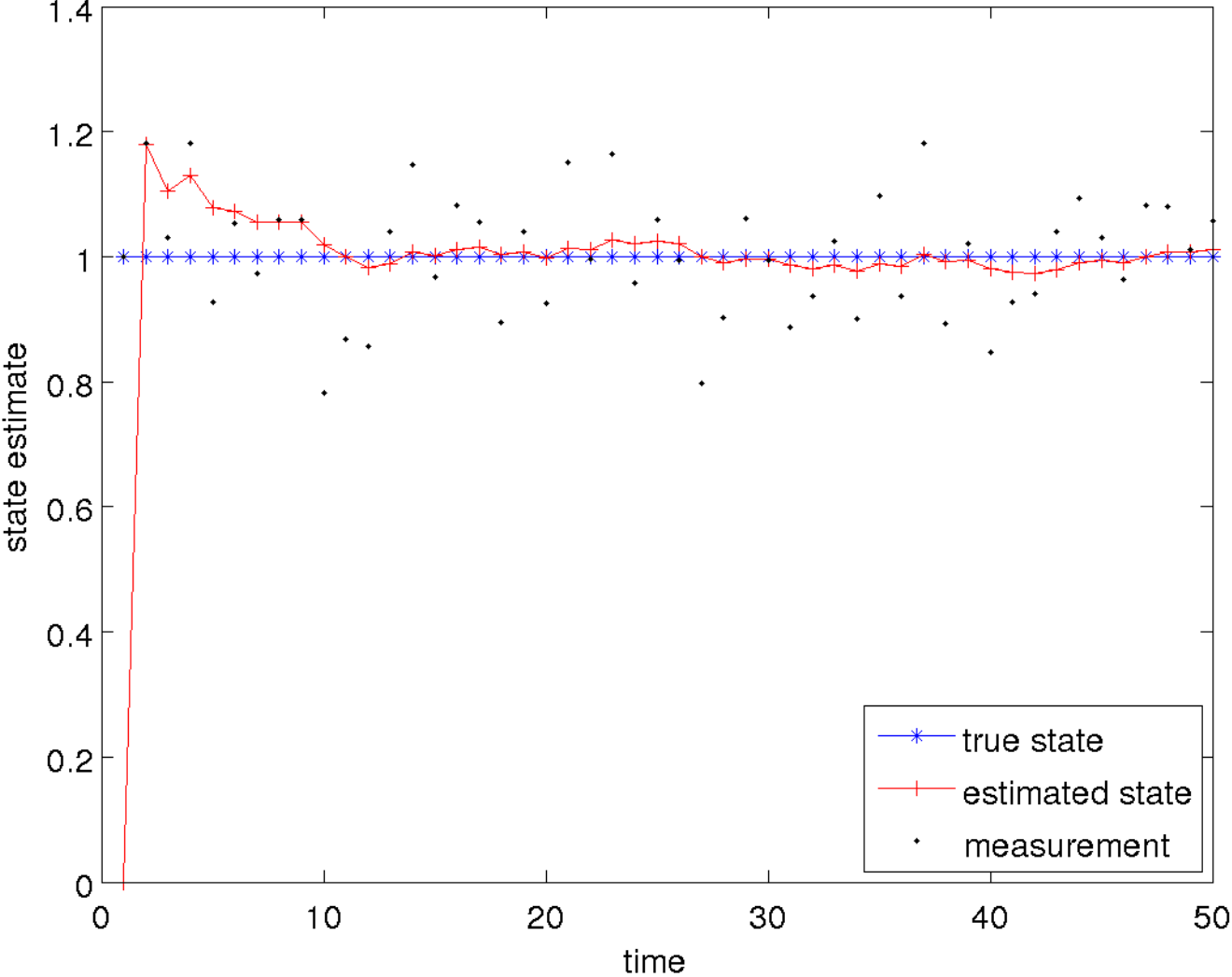
# Tank of Water

- ▶ estimate the level of water in the tank; the water could be
  - ▶ static, filling, or emptying
  - ▶ not sloshing or sloshing





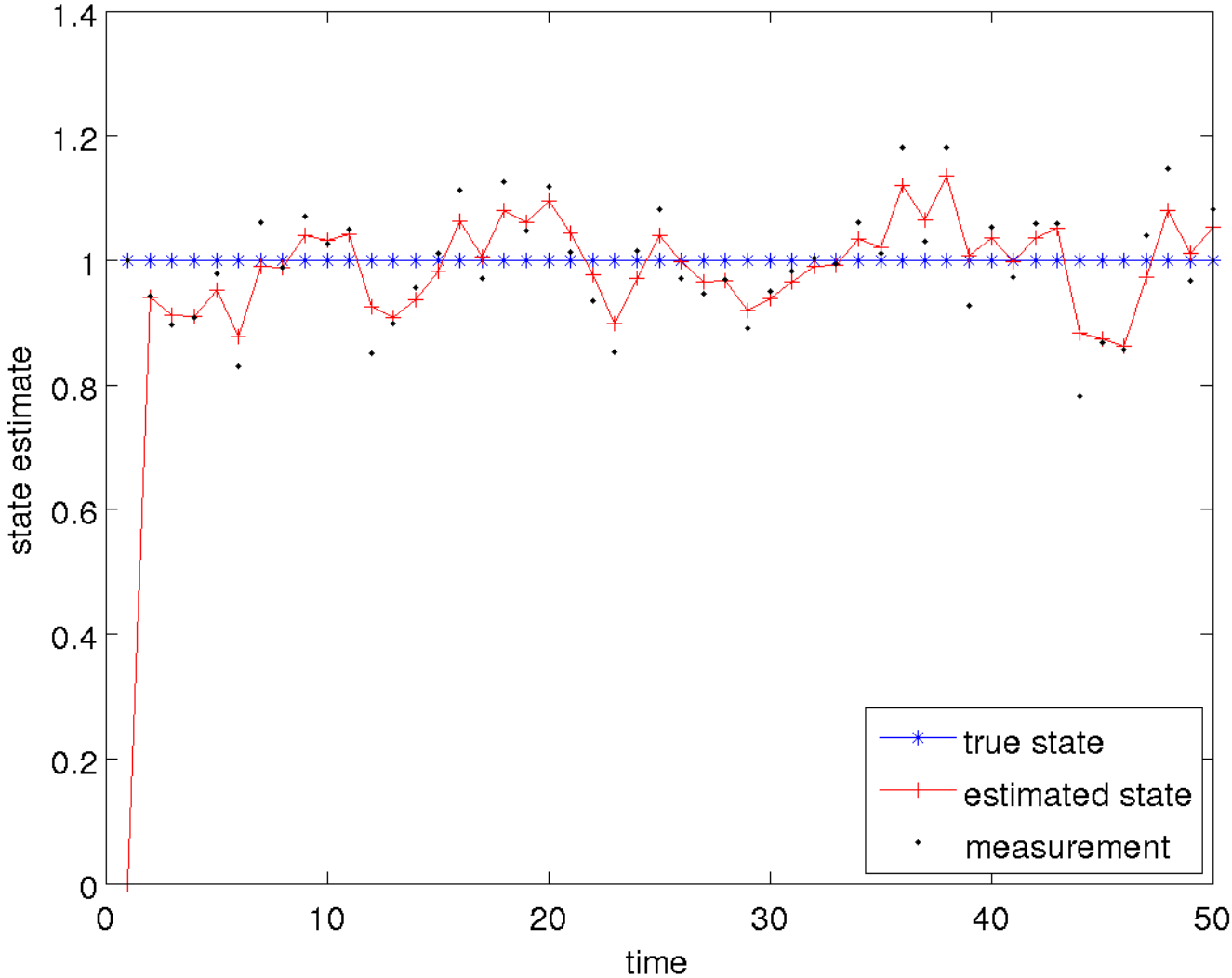
# Tank of Water: Static and Not Sloshing



# Tank of Water: Static and Not Sloshing

- ▶ notice that in this case the Kalman filter tends towards estimating a constant level because the plant noise covariance is small compared to the measurement noise covariance
  - ▶ the estimated state is much smoother than the measurements
- ▶ what happens if we increase the plant noise covariance?

# Tank of Water: Filling and Not Sloshing



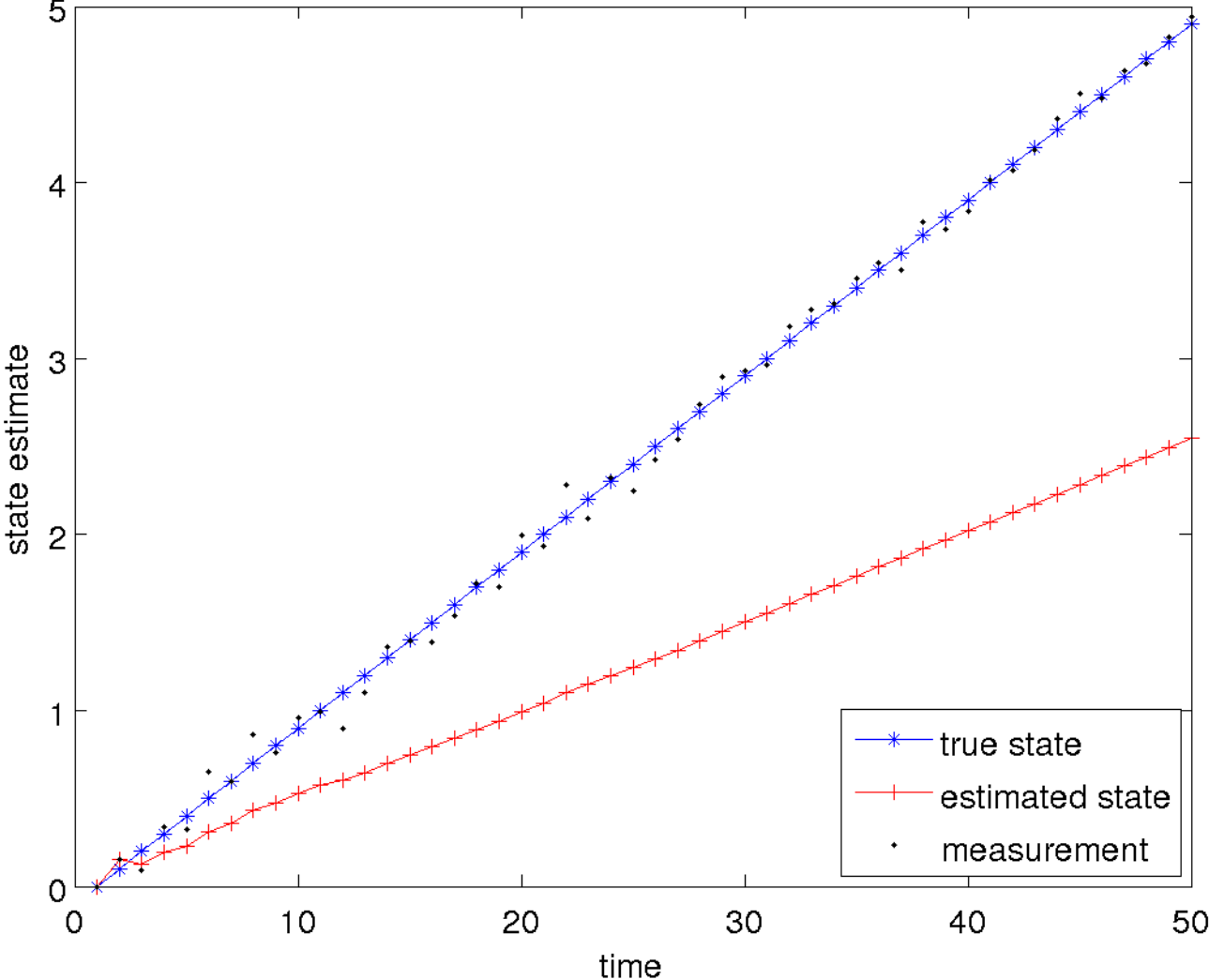
# Tank of Water: Static and Not Sloshing

- ▶ notice that in this case the Kalman filter tends towards estimating values that are closer to the measurements
- ▶ increasing the plant noise covariance causes the filter to place more weight on the measurements

# Tank of Water: Filling and not Sloshing

- ▶ suppose the true situation is that the tank is filling at a constant rate but we use the static tank plant model
  - ▶ i.e., we have a plant model that does not accurately model the state transition

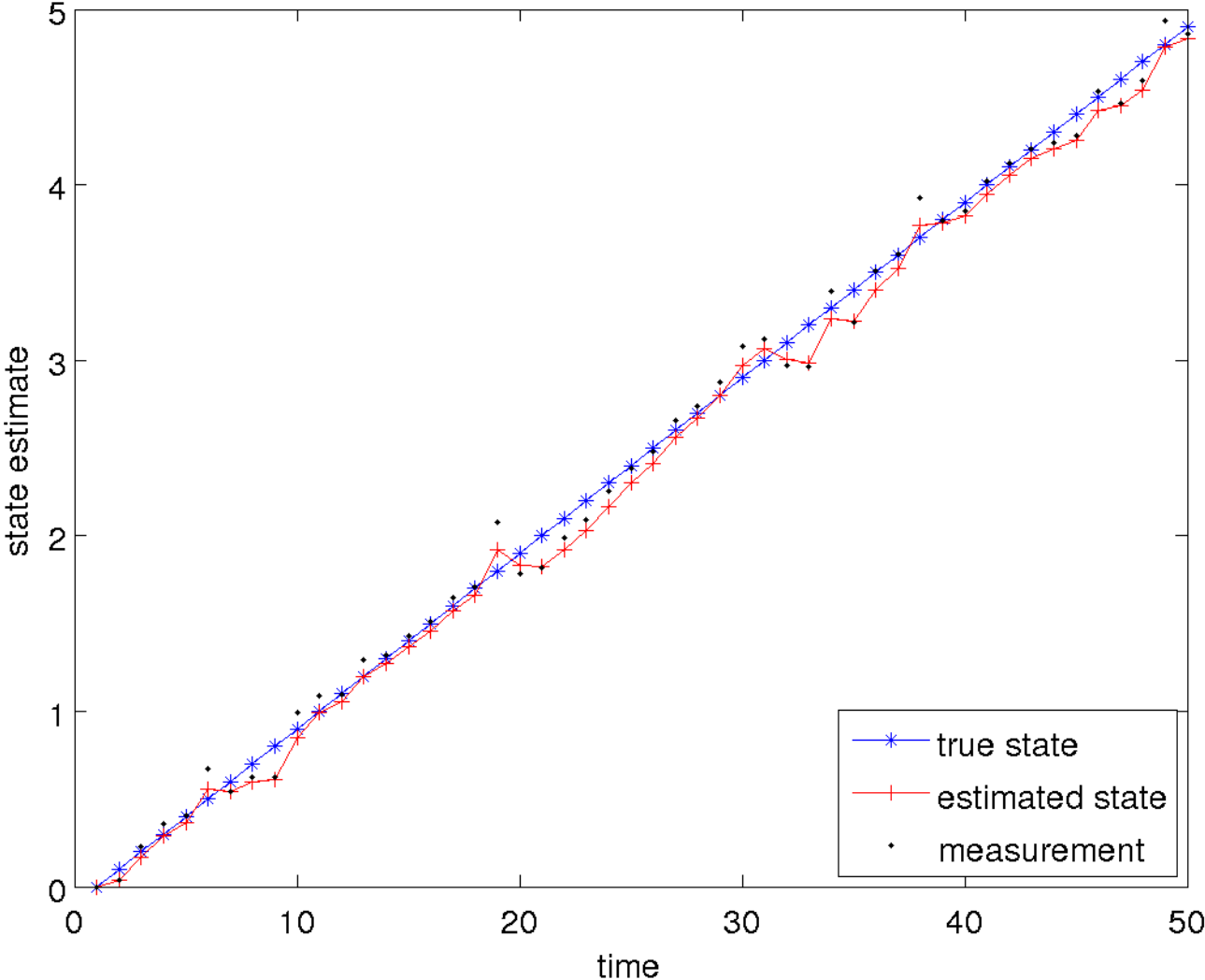
# Tank of Water: Filling and not Sloshing



# Tank of Water: Filling and not Sloshing

- ▶ notice that in this case the estimated state trails behind the true level
  - ▶ estimated state has a much greater error than the noisy measurements
- ▶ if the plant model does not accurately model reality than you can expect poor results
  - ▶ however, increasing the plant noise covariance will allow the filter to weight the measurements more heavily in the estimation...

# Tank of Water: Filling and not Sloshing

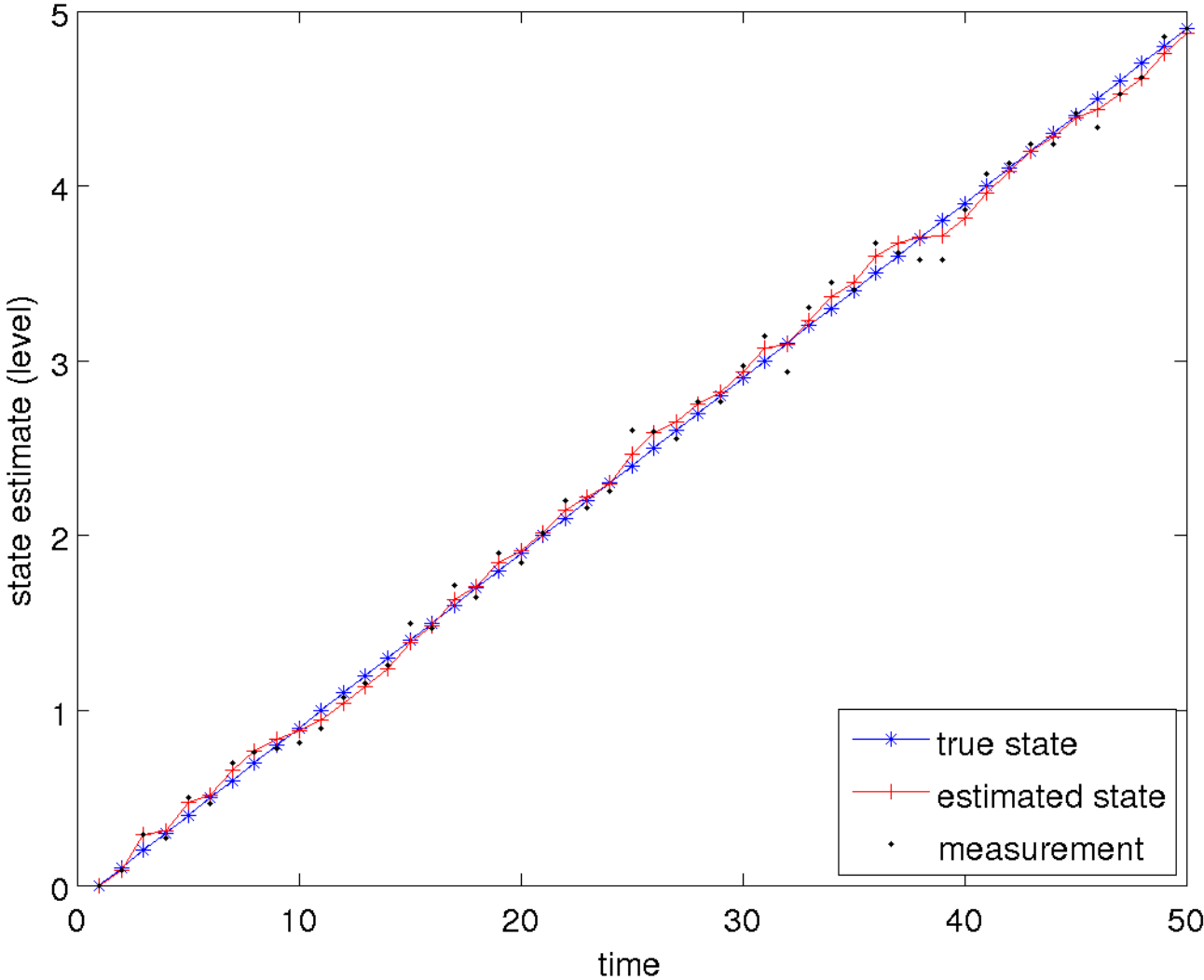




# Tank of Water: Filling and not Sloshing

- ▶ it is not clear if we have gained anything in this case
  - ▶ the estimated state is reasonable but it is not clear if it is more accurate than the measurements
- ▶ what happens if we change the plant model to more accurately reflect the filling?

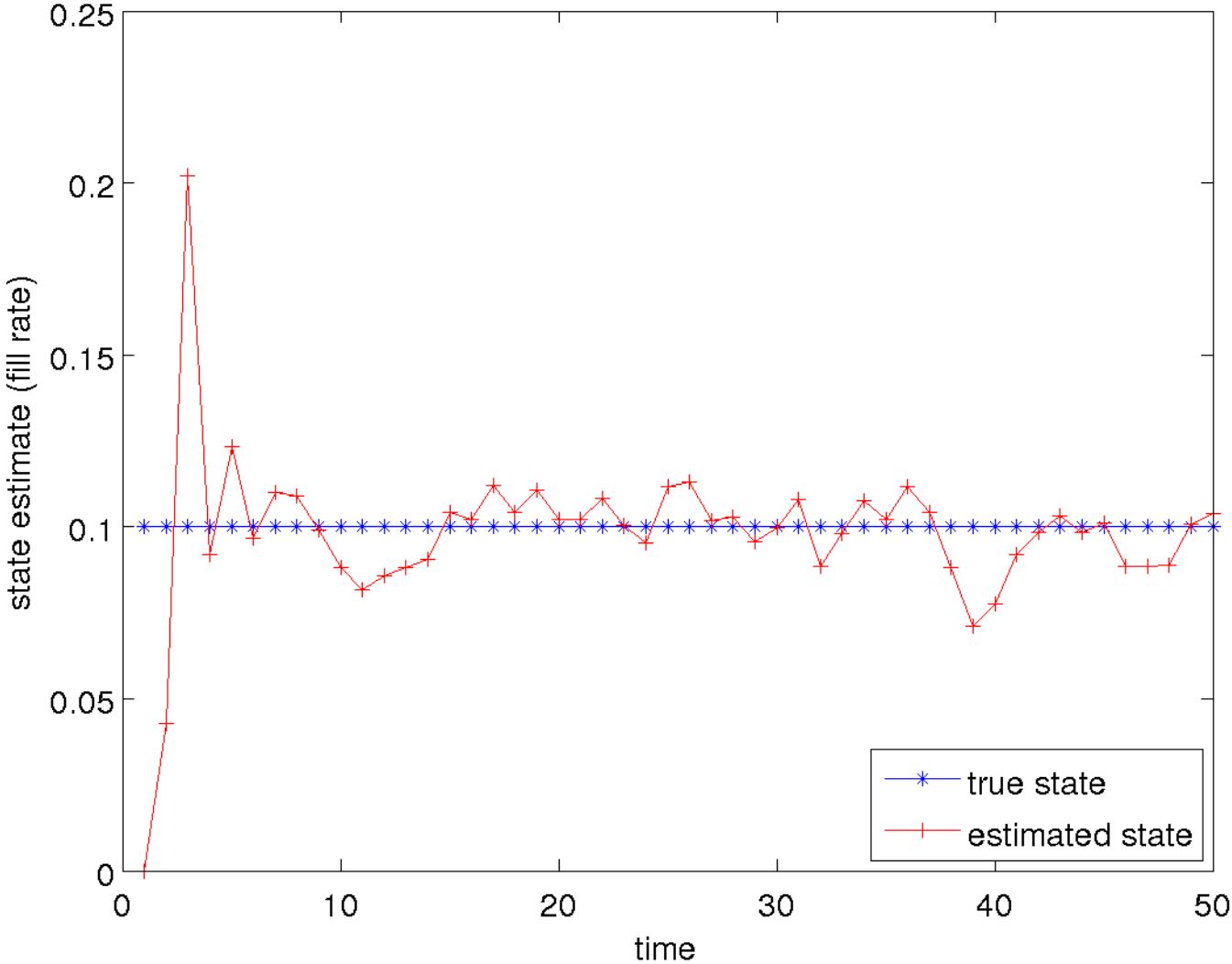
# Tank of Water: Filling and not Sloshing



# Tank of Water: Filling and not Sloshing

- ▶ notice that the estimated state is more accurate and smoother than the measurements
- ▶ what about the filling rate?

# Tank of Water: Filling and not Sloshing



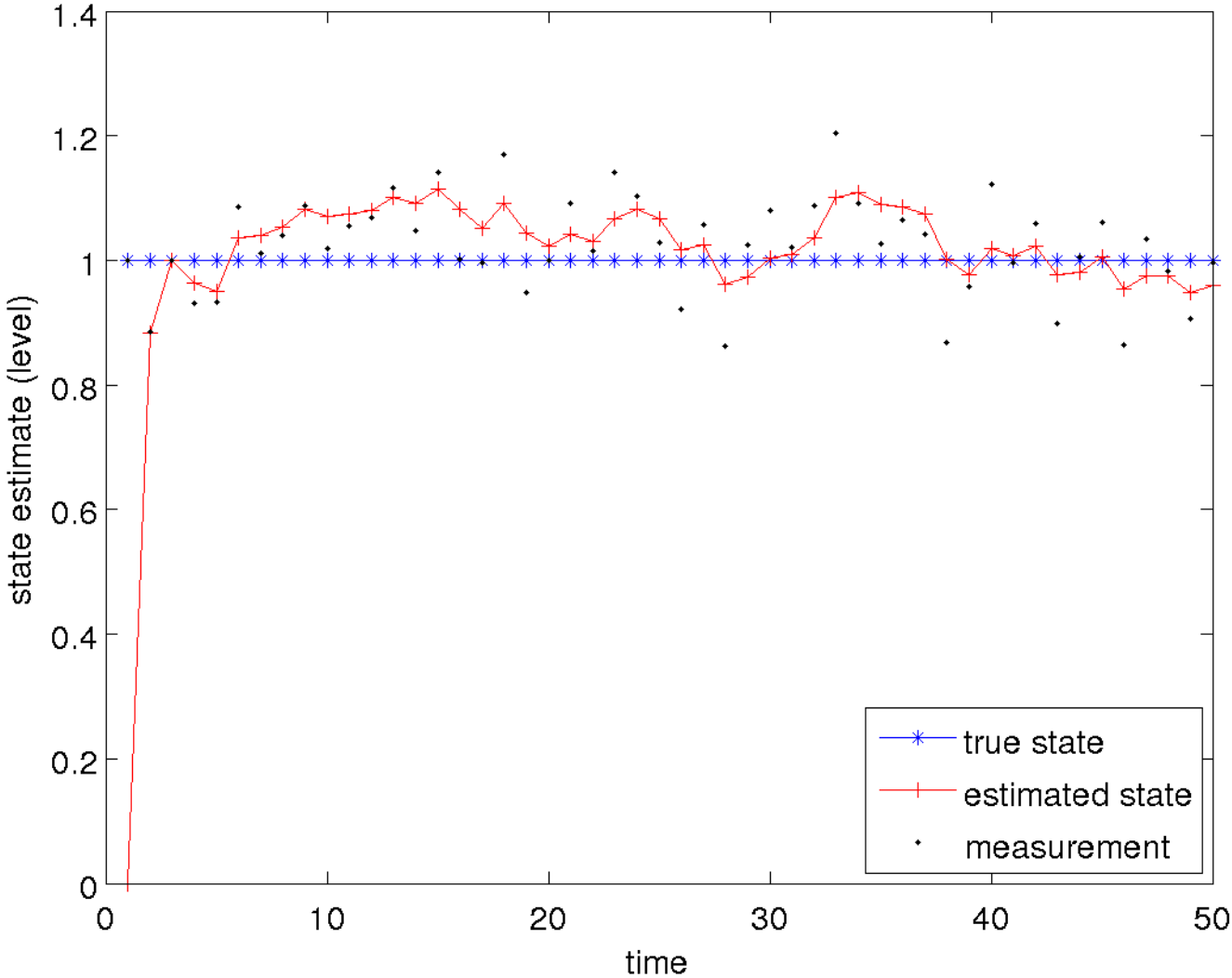
# Tank of Water: Filling and not Sloshing

- ▶ notice that the estimated filling rate seems to jump more than the estimated level
  - ▶ this should not be surprising as we never actually measure the filling rate directly
    - ▶ it is being inferred from the measured level (which is quite noisy)

# Tank of Water: Static and not Sloshing

- ▶ can we trick the filter by using the filling plant model when the level is static?
  - ▶ hopefully not, as the filter should converge to a fill rate of zero!

# Tank of Water: Static and not Sloshing



# Tank of Water: Static and not Sloshing

