# Day 23

#### Kalman Filter Examples

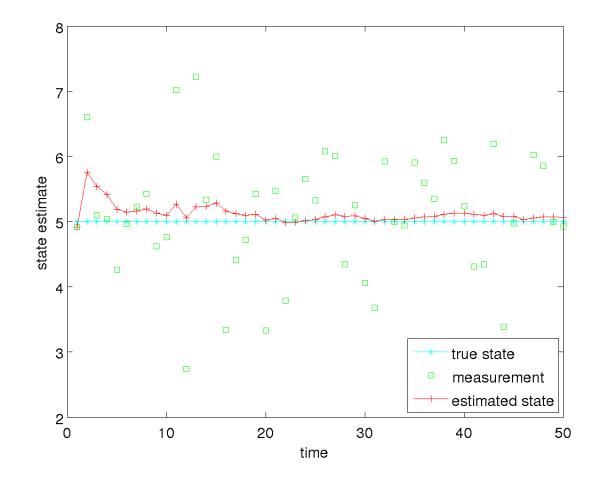
- recall the static state estimation problem we have been studying
  - the process or plant model

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

the observation model

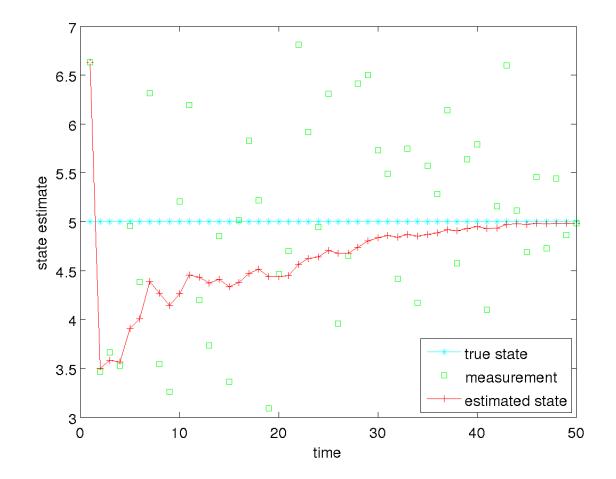
$$C_t = 1, \quad Q_t = \sigma_t^2 \qquad \qquad z_t = x_t + \delta_t$$

how well does the Kalman filter work

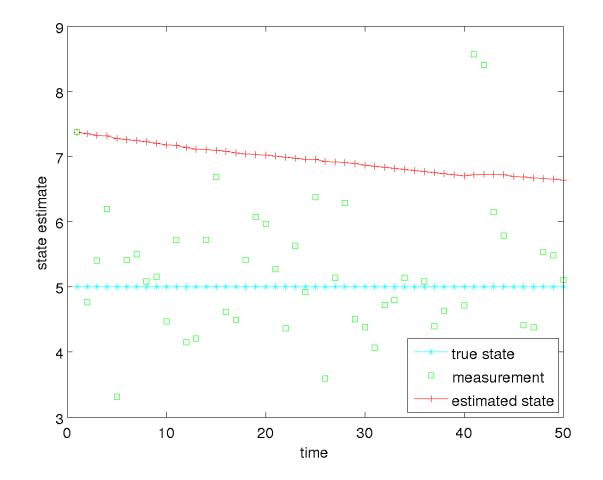


- notice that we need to specify the measurement noise covariance  $Q_t$
- how sensitive is the Kalman filter to  $Q_t$ ?
  - e.g., what if we use a  $Q_t$  that is much smaller than the actual measurement noise?
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• specified  $Q_t = 0.01 * \operatorname{actual} Q_t$ 

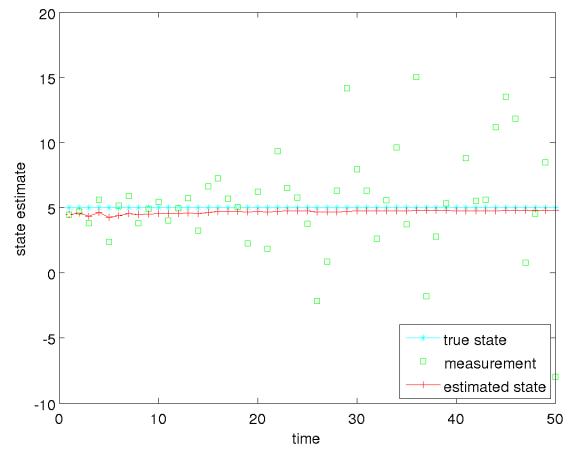


• specified  $Q_t = 100 * \text{actual } Q_t$ 



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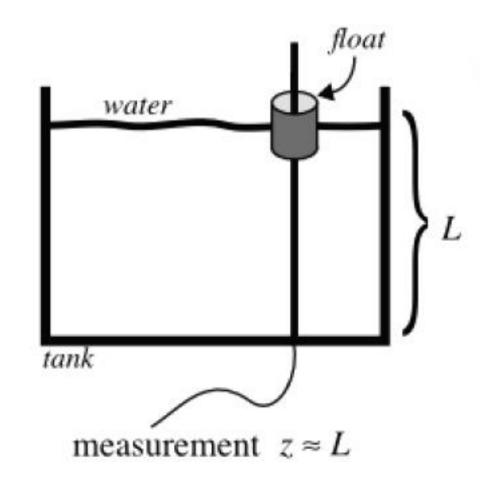
 suppose our measurements get progressively noisier over time



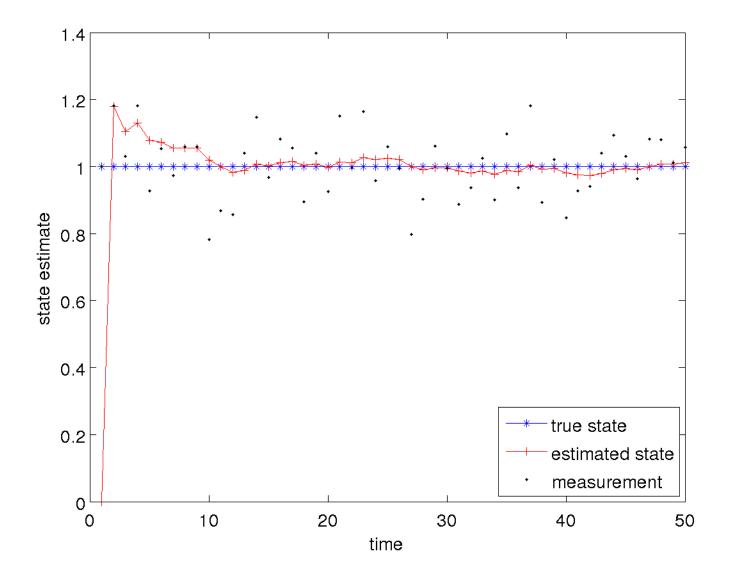
noise variance increases 10% for each successive measurement

### Tank of Water

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

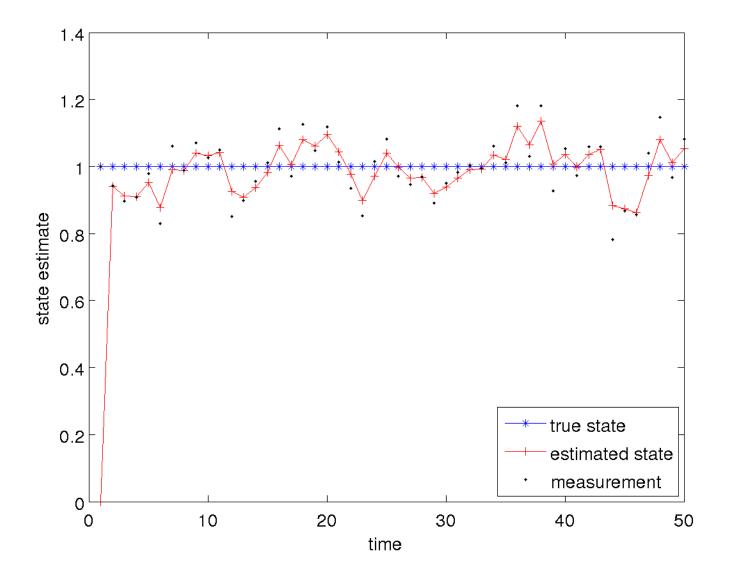


#### Tank of Water: Static and Not Sloshing



# Tank of Water: Static and Not Sloshing

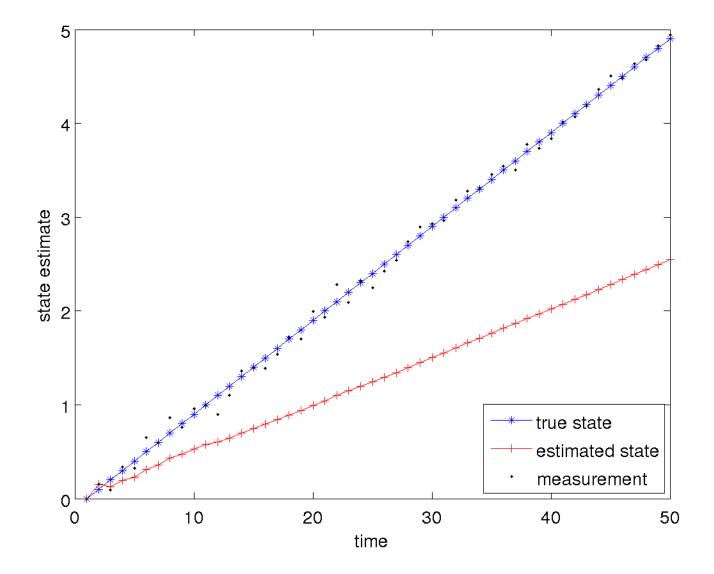
- notice that in this case the Kalman filter tends towards estimating a constant level because the plant noise covariance is small compared to the measurement noise covariance
  - the estimated state is much smoother than the measurements
- what happens if we increase the plant noise covariance?



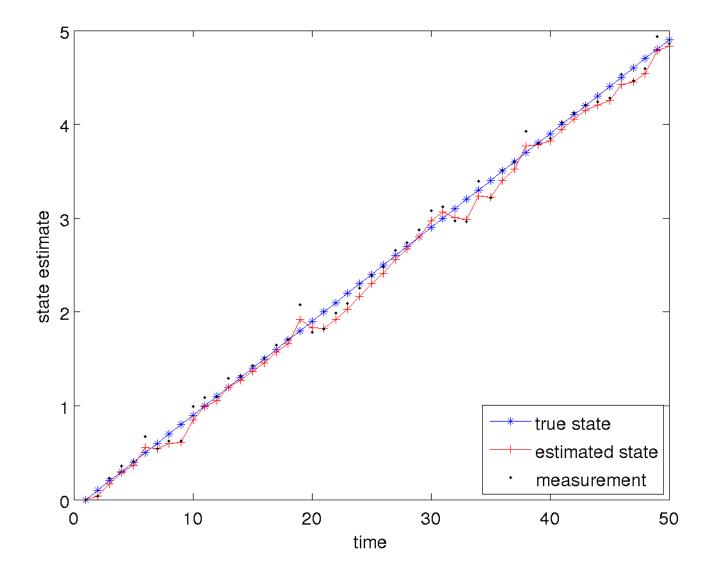
# Tank of Water: Static and Not Sloshing

- 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

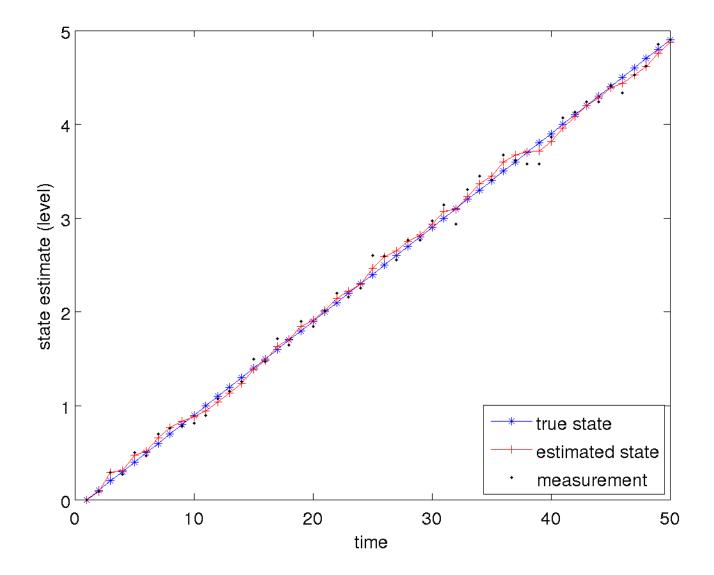
- suppose the true situation is that the tank is filling at a constant rate but we use the static tank plant model
  - i.e., we have a plant model that does not accurately model the state transition



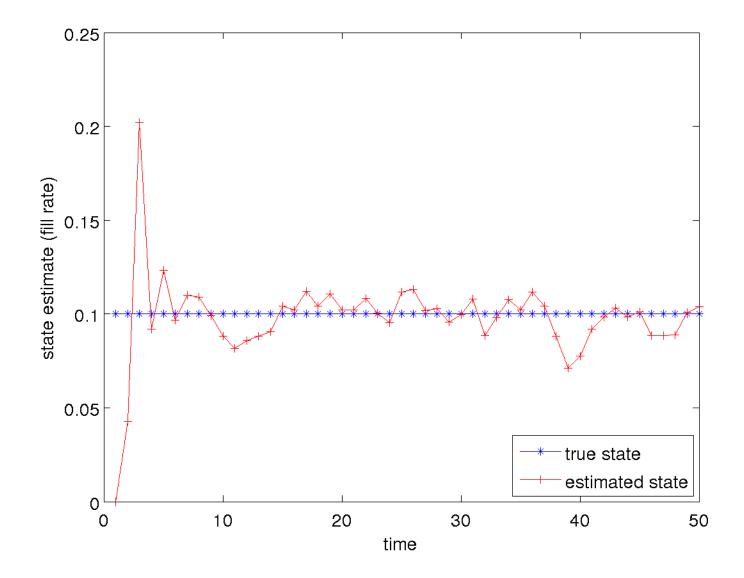
- notice that in this case the estimated state trails behind the true level
  - estimated state has a much greater error than the noisy measurements
- if the plant model does not accurately model reality than you can expect poor results
  - however, increasing the plant noise covariance will allow the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



- 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?



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

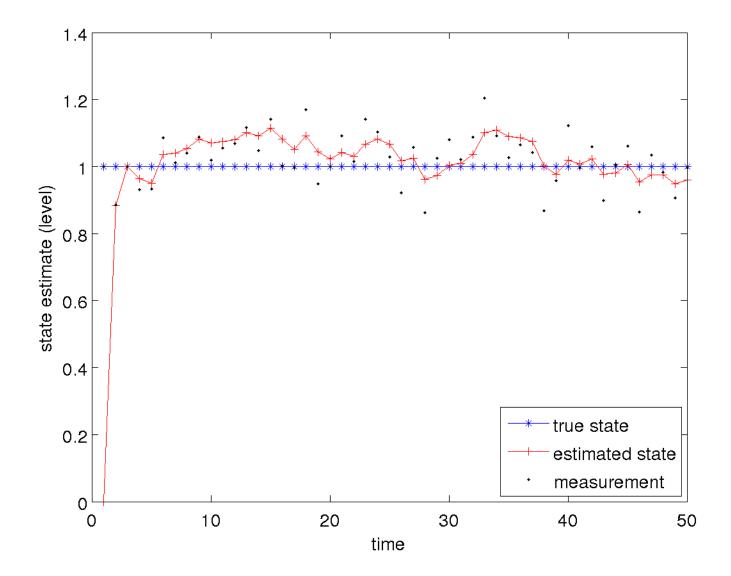


- notice that the estimated filling rate seems to jump more than the estimated level
  - this should not be surprising as we never actually measure the filling rate directly
    - > it is being inferred from the measured level (which is quite noisy)

# 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

