Vehicle Localization with Kalman Filters

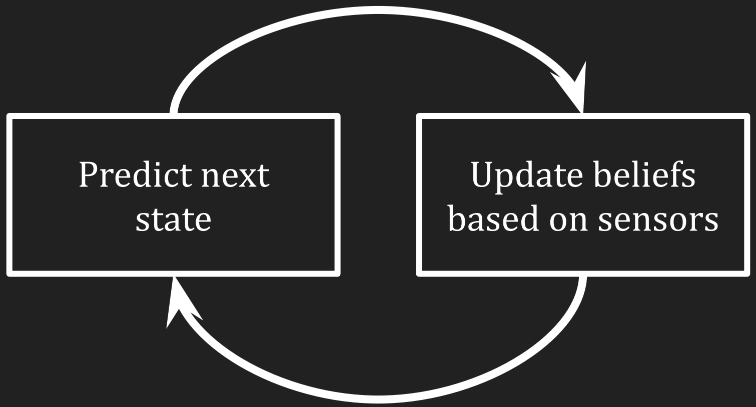
Noah Mollerstuen

Project Objective

- Estimate a robot's position in the presence of uncertainty
- Integrate information from diverse sensors
  - GPS (low precision, slow)
  - Accelerometer (fast, drifts over time)
- How can we optimally update our beliefs in the presence of conflicting and uncertain sensor measurements?

Kalman Filters

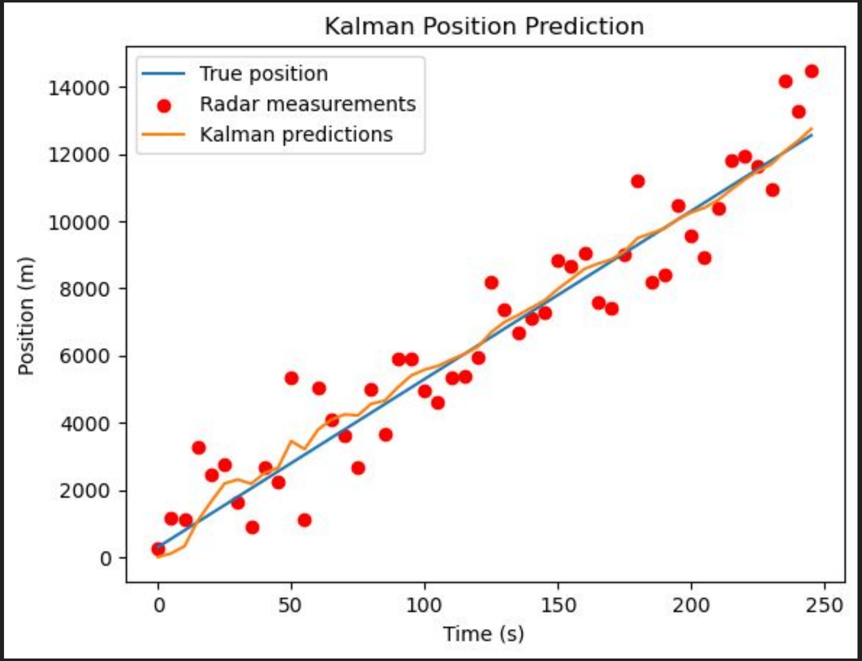
1. Model robot (or other system) as a set of linear differential equations
2. Given probability distribution of initial states, predict next state based on dynamic model
3. Use sensors as evidence to update beliefs in Bayesian fashion
4. Repeat

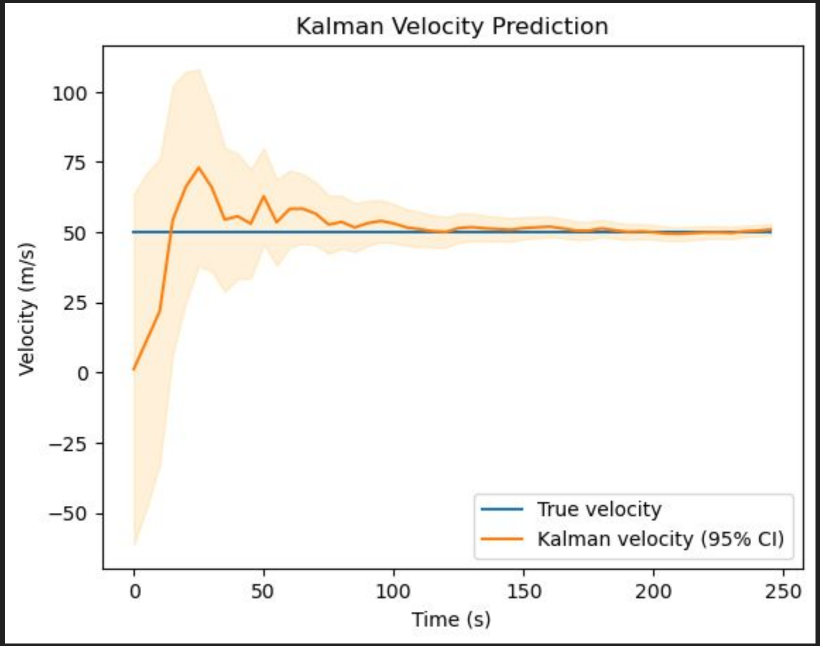


Testing Environment

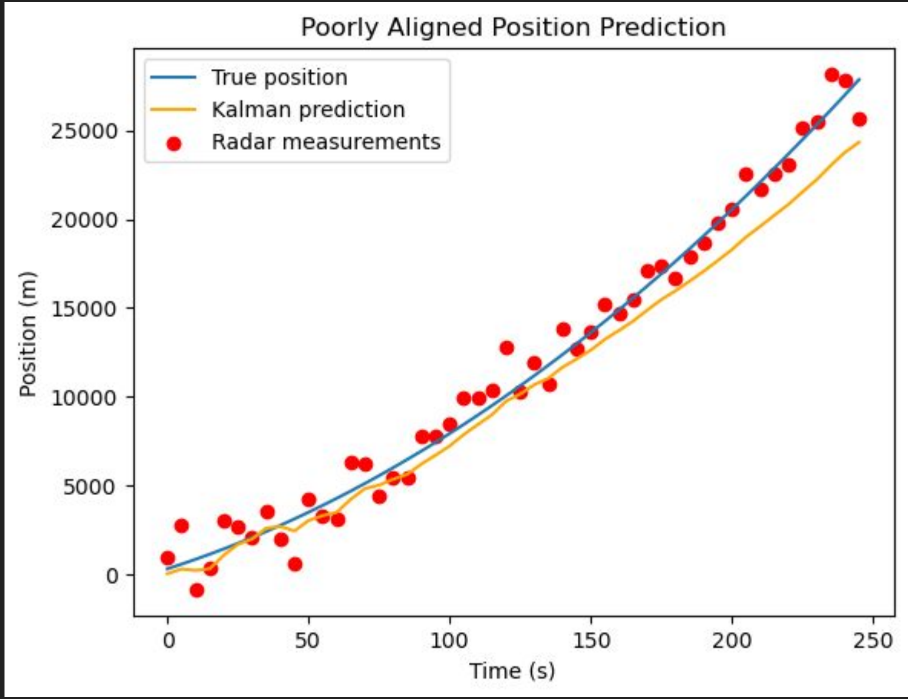
- Model position and velocity of an aircraft in one dimension
- Measure position with simulated radar (gaussian sampling)
- Track estimated position, estimated velocity, and the variance and covariance for each
- For each radar measurement:
  - Predict the new position of the aircraft based on the passage of time
  - Combine that prediction with the radar's uncertain measurement

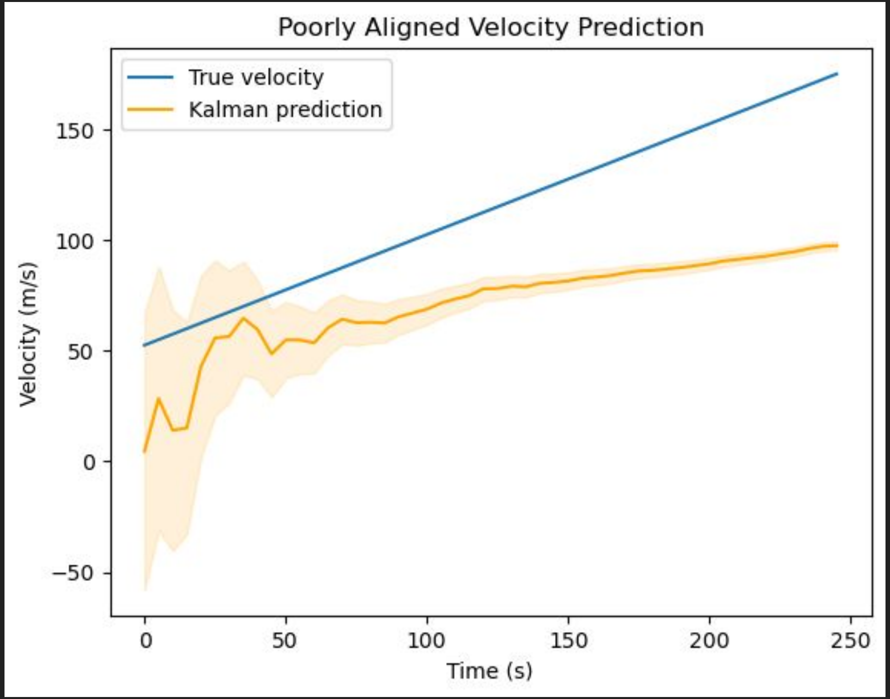
Results


Kalman Position Prediction
True position
Radar measurements
Kalman predictions
14000
12000
10000
8000
6000
4000
2000
0
Position (m)
0
50
100
150
200
250
Time (s)

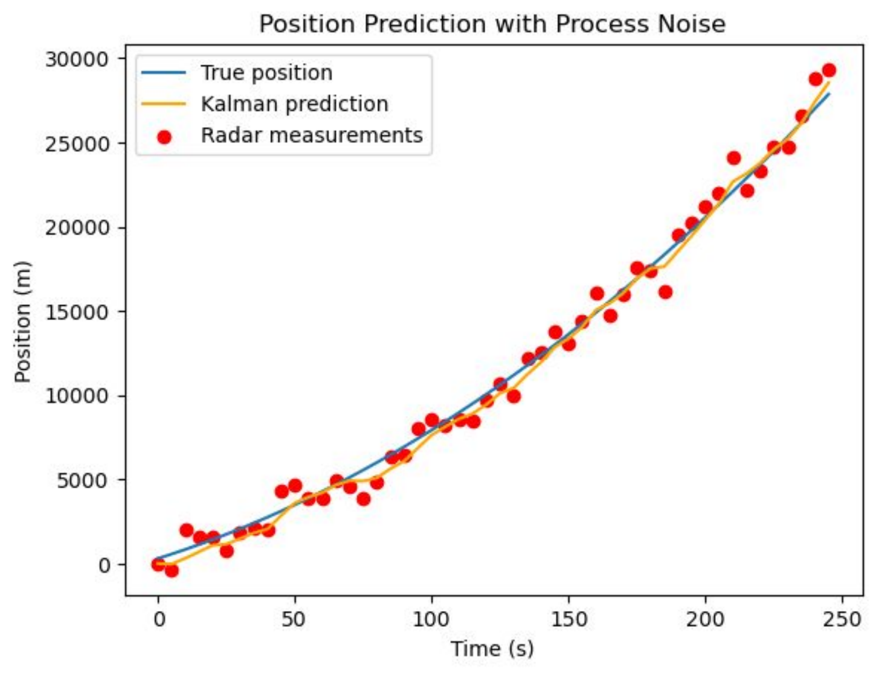

Kalman Velocity Prediction
100
75
50
25
0
−25
−50
Velocity (m/s)
True velocity
Kalman velocity (95% CI)
0
50
100
150
200
250
Time (s)

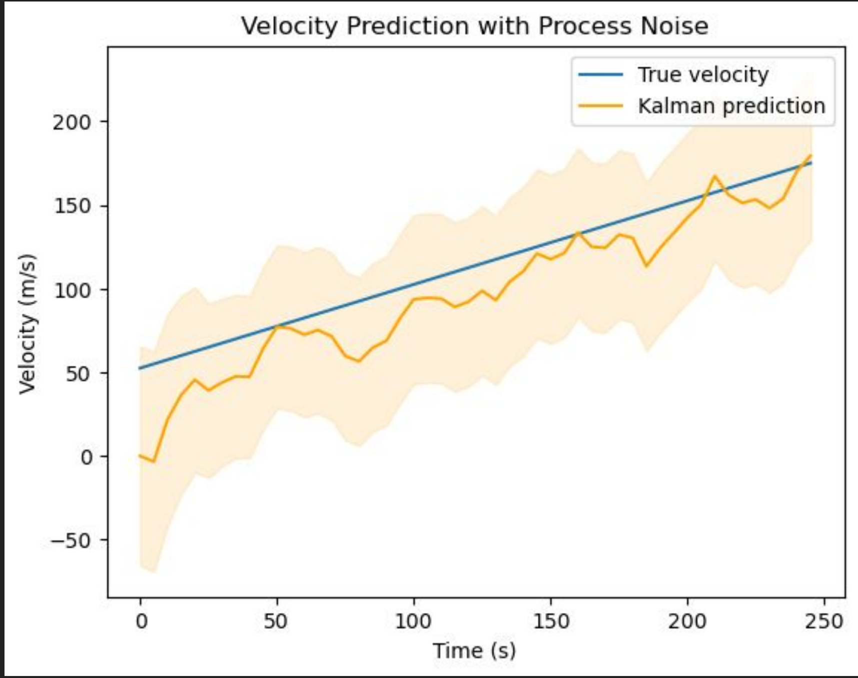
Model Uncertainty





Process Noise





Takeaways

- The Kalman filter accurately tracks the plane’s position despite noisy measurements
- The filter can accurately predict the plane’s velocity despite having no direct way to measure it
- These capabilities rely on an accurate model of the dynamical system

Future Work

- Extend localization into multiple dimensions
- Improve robustness to differences between the physical model of the Kalman filter and the behavior of the system