OTTO VON GUERICKE UNIVERSITÄT MAGDEBURG

INF FAKULTÄT FÜR INFORMATIK

Object Detection and Fusion in a Camera Network

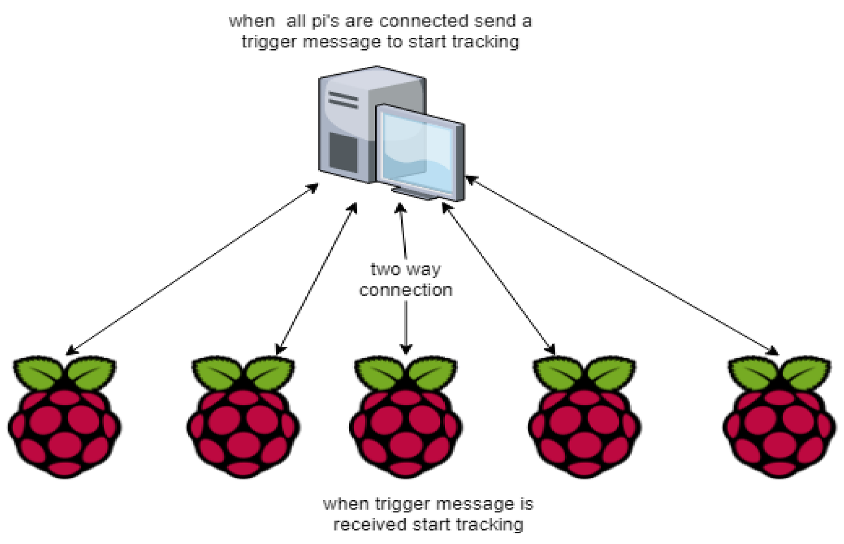
Introduction

The goal of the project is to combine Multiple measurements from a distributed sensor network, gathered centrally and fused to produce a location estimate with less uncertainty than one obtainable from only a single sensor.

Five raspberry pi powered cameras mounted on a frame aimed at the ground are employed to track an object which is moving in a circular path at a constant angular velocity at regular time intervals.

These images are used to detect the position of the object using an object detection algorithm and are used together in an estimation algorithm to approximate the Motion model of the object in the scene.

Methods



Pi inter-communication

Arrangement of the Camera network

The Object detection is carried out using the OpenCV Corner-Harris object detection algorithm to estimate the object location in the camera coordinates and then transformed to a global coordinate system.

A constant turn model with state variables X-coordinate(x), Y-coordinate(y), velocity components in X and Y-direction (Vx and Vy) is defined. The Kalman filter algorithm produces an estimate of hidden variables based o inaccurate and uncertain measurements. So the coordinates obtained from object detection are used in the Kalman filter algorithm to approximate the object motion model.

The angular velocity of the object is measured manually from the images captured at regular intervals.

The process covariance is initialized based on the prior research and the Measurement covariance is initialized based on the variance observed in the sensor measurements.

Prediction

Project the state ahead

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

Project the error covariance ahead

$$P_{k+1} = AP_kA^T + Q$$

Correction

Compute the Kalman Gain

$$K_k = P_kH^T(HP_kH^T + R)^{-1}$$

Update the estimate via measurement

$$x_k = x_k + K_k(z_k - Hx_k)$$

Update the error covariance

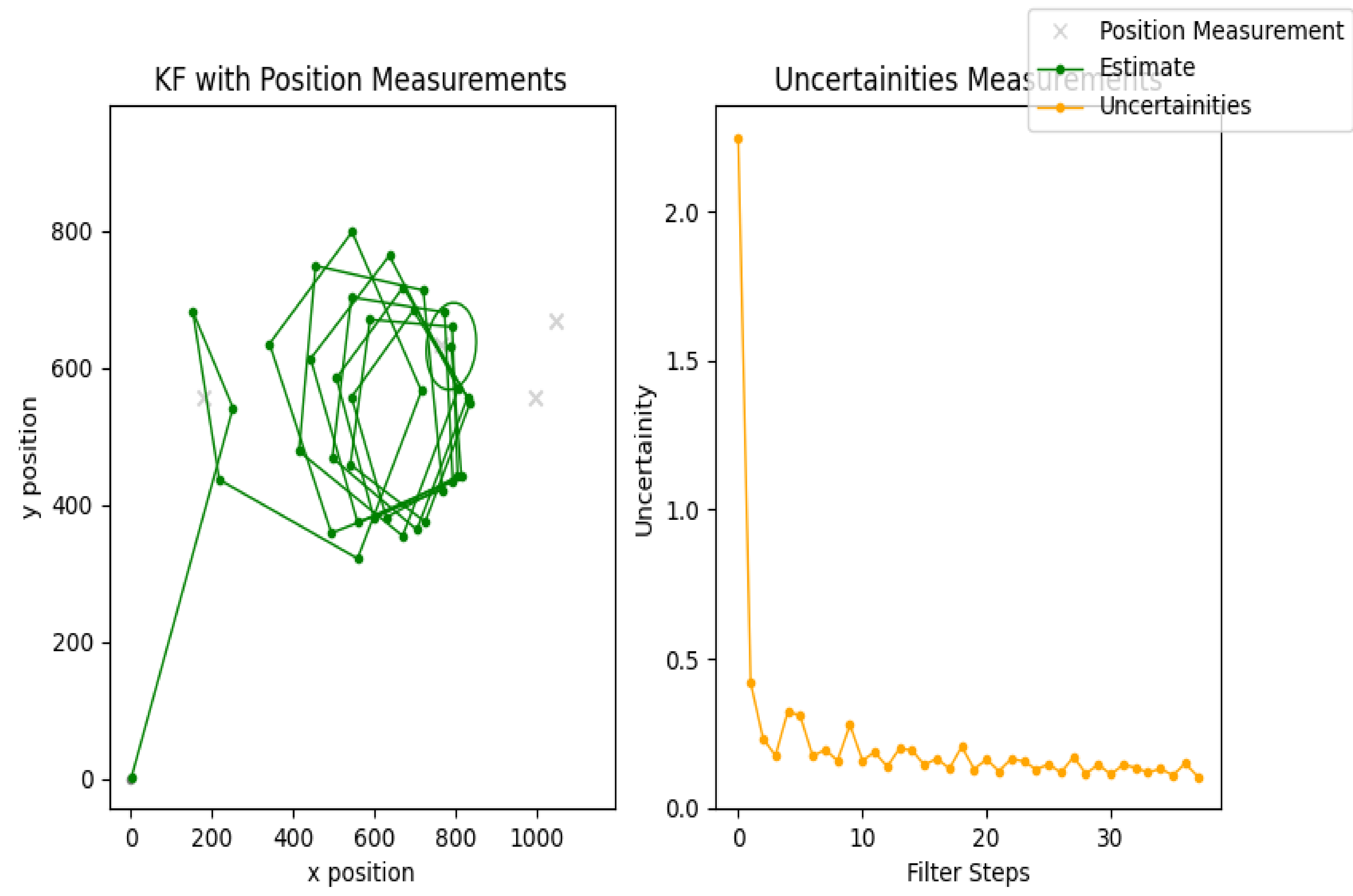
$$P_k = (I - K_kH)P_k$$

Initialize R, P, Q once

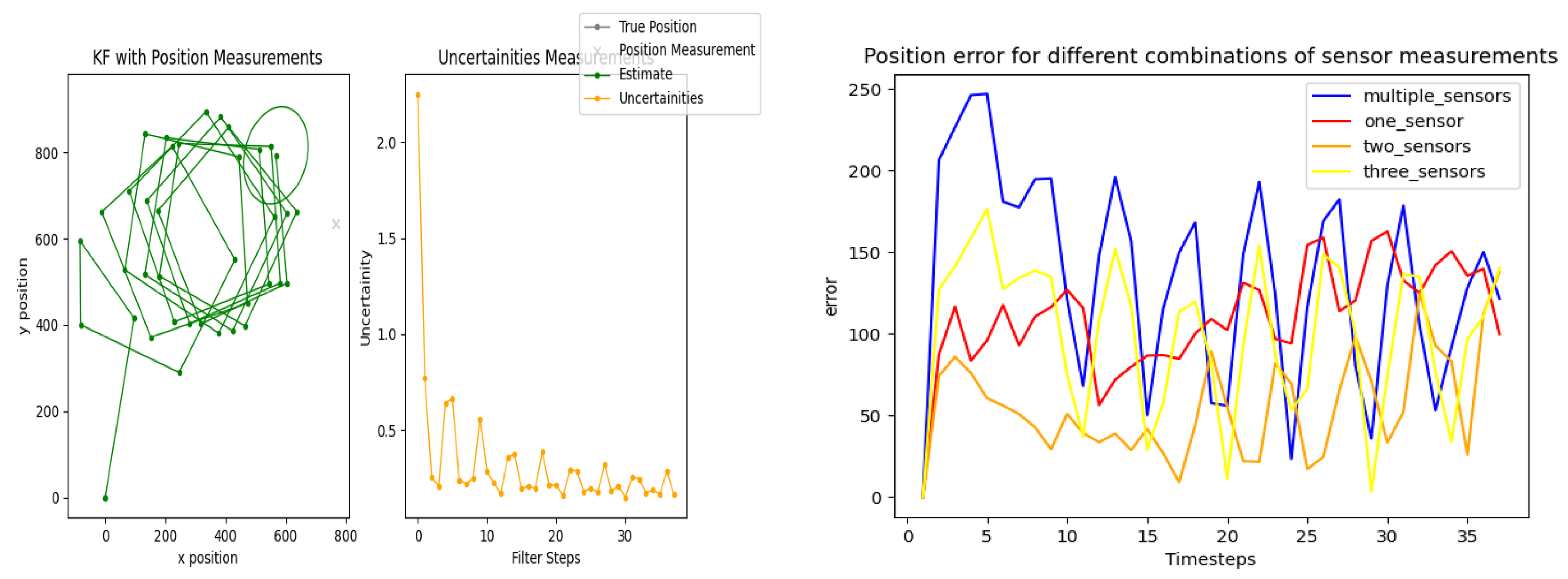
R is the measurement Covariance
Q is the Process Covariance
P is the State estimate Covariance
H is the Measurement Matrix
A is the State Transition matrix (depends on the model choice)
K_k is the Kalman Gain

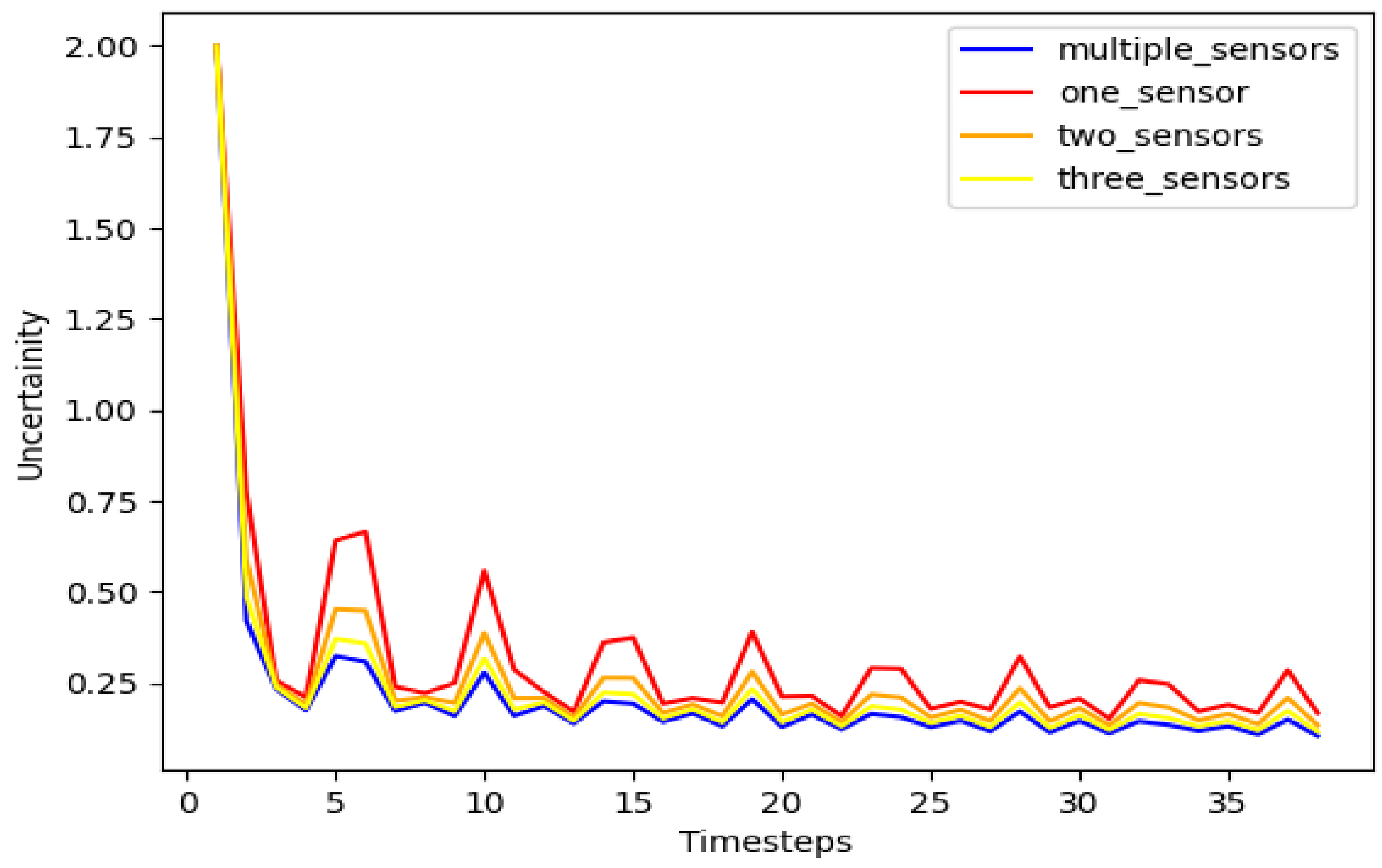
For each iteration, the state estimate is updated as many times as there are sensor measurements in that time step

Results



Validation





Uncertainty decay when different combinations of sensor measurements

Conclusion

It is quite evident from the plots above that the overall uncertainty of our state estimates diminishes quickly when multiple sensor measurements are available.

The uncertainty decreases smoothly in the case of multiple measurements whereas in the case of a single measurement there are fluctuations during the iterations.

The balance between the Process and Measurement Covariance is essential for a quick convergence of the model.

If any of the multiple sensor data has a huge bias, a High bias is observed in the overall state estimate when more than one measurement is used.