

Homework 5

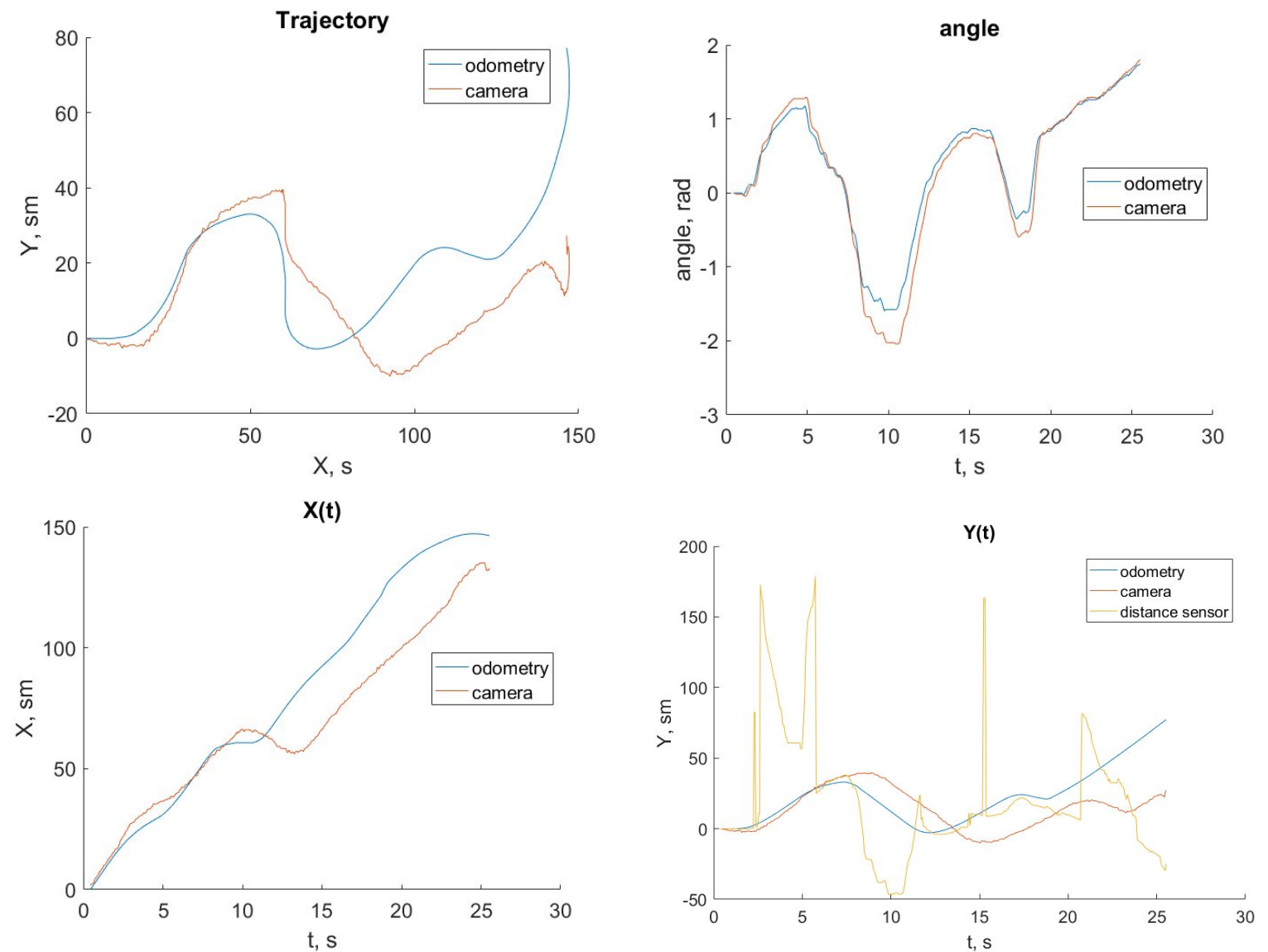
System Identification and Simulation

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My partner is Ruslan Rezin. He gives me data from 4 sensors: camera, wheels angle rate, gyro sensor and distance sensor. Data were taken from differential robot.

Camera provide information about position of the robot, X and Y coordinates. Wheels angle rate gives the odometry information by that it is possible to calculate the robot position and orientation. Data from gyro sensor show the orientation of the robot. The combination of gyro and distance sensor gives the information of Y coordinate.

Plots of initial data.



For sensors, we take the following sigma values:

sigmaCamera=1 sm;
sigmaDist=10 sm;
sigmaAngle=5 deg;

sigmaOd=1 sm;
sigmaOdAngle=5 deg;
sigmaRobot=1

However, as seen from the graph of Y (t), the value from the distance sensor shows incorrect values for values greater than 50, so in these cases sigmaDist = inf.

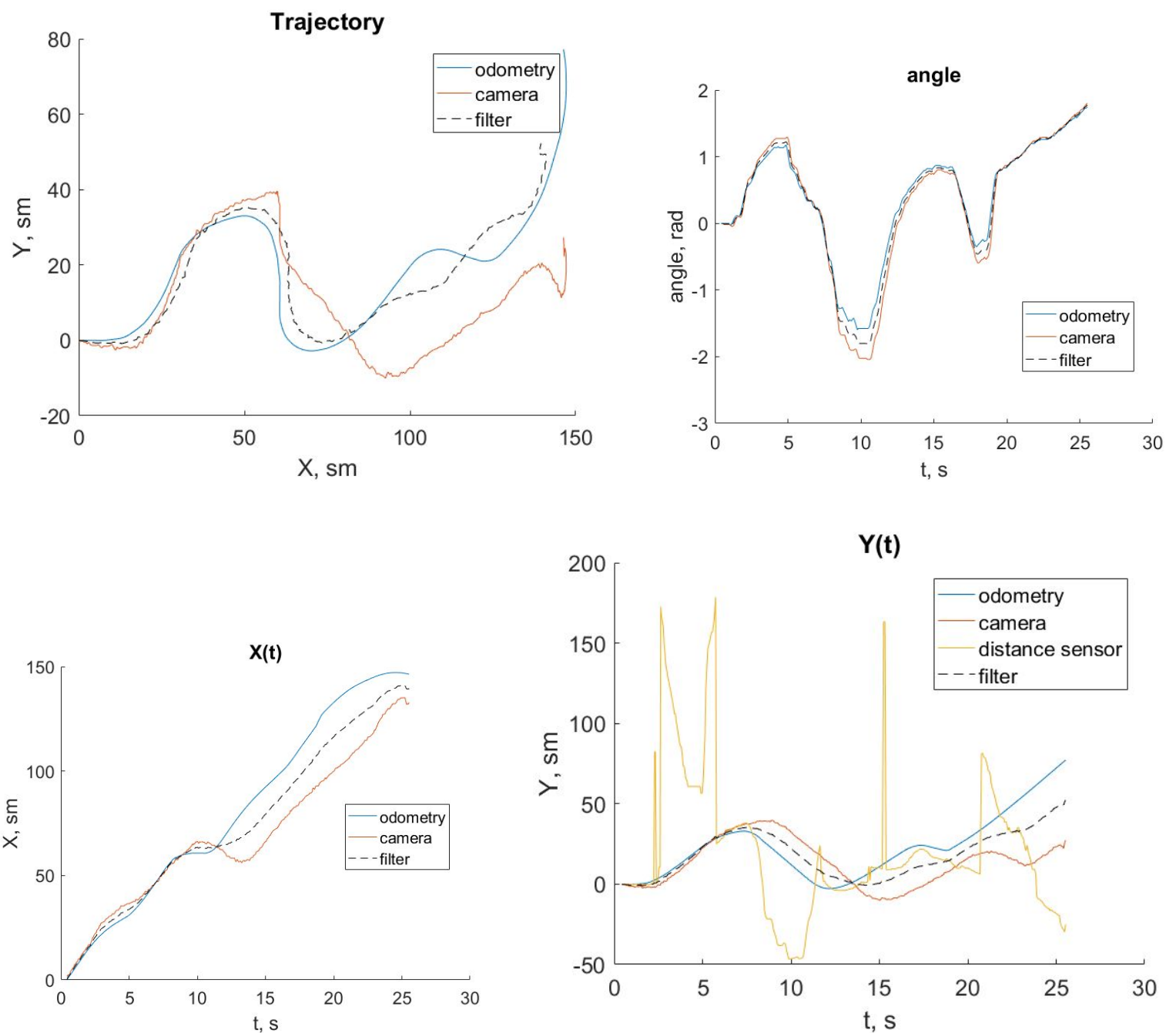
Mean and standard deviation

First variant for data fusing is mean and standard deviation a calculation. For fusing 2 variants of data we can apply following equations:

$$\mu = [\sigma_{z_2}^2 / (\sigma_{z_1}^2 + \sigma_{z_2}^2)]z_1 + [\sigma_{z_1}^2 / (\sigma_{z_1}^2 + \sigma_{z_2}^2)]z_2$$

$$1/\sigma^2 = (1/\sigma_{z_1}^2) + (1/\sigma_{z_2}^2)$$

Results:



Kalman filter

We do not have data of the control signal U for the robot, therefore we will take the prediction: the position of the robot is equal to the previous one.

$$m(t)=m(t-1),$$

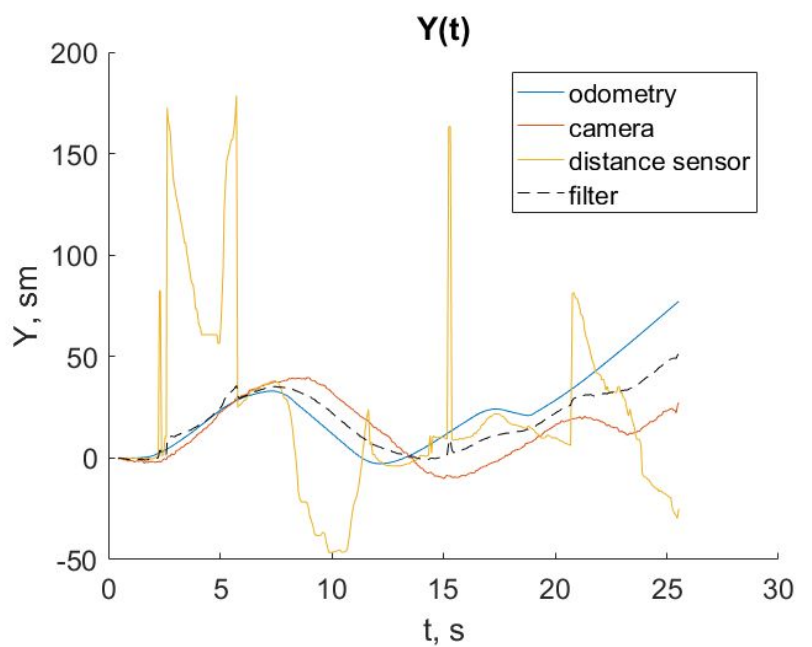
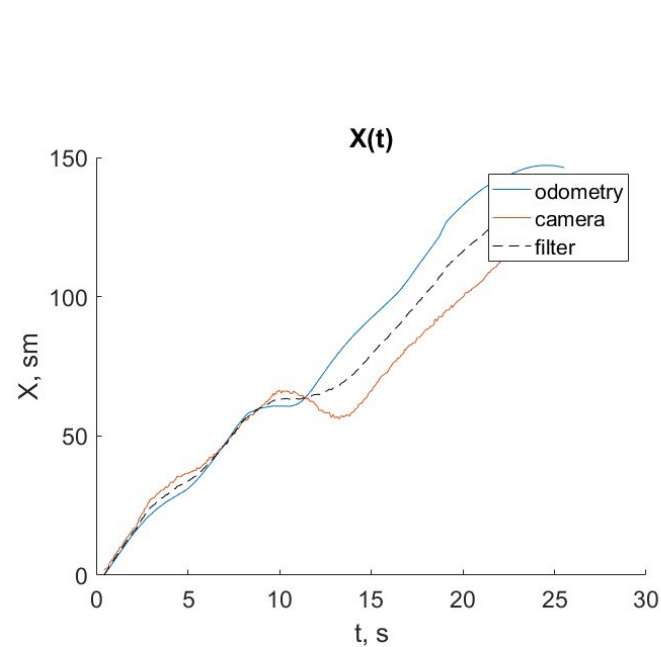
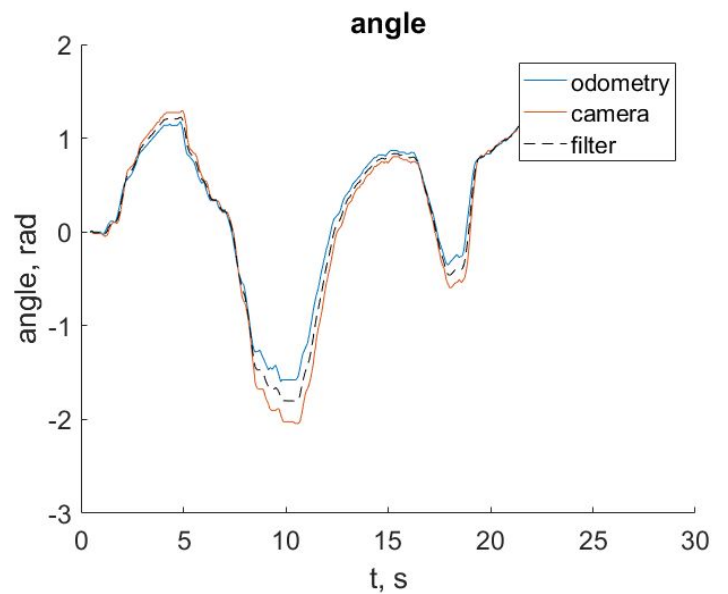
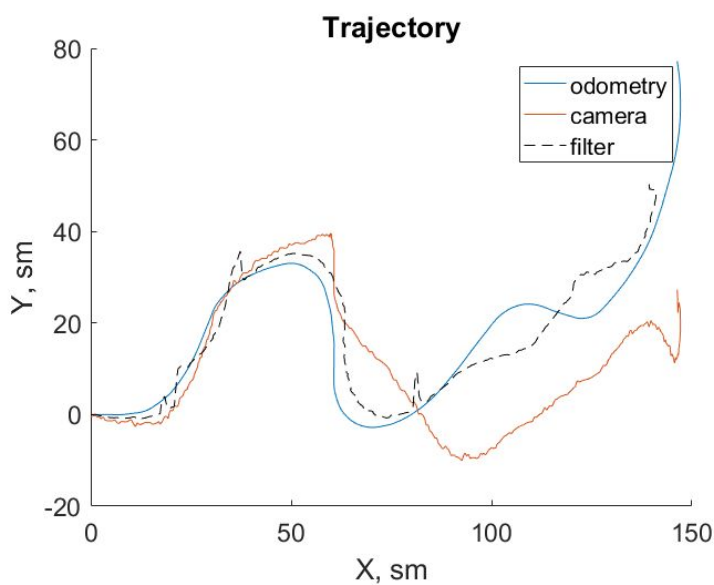
$$m=\{X, Y, \theta\}$$

This model is linear, so you can apply the Kalman filter. The usage of other filters in this case does not make sense.

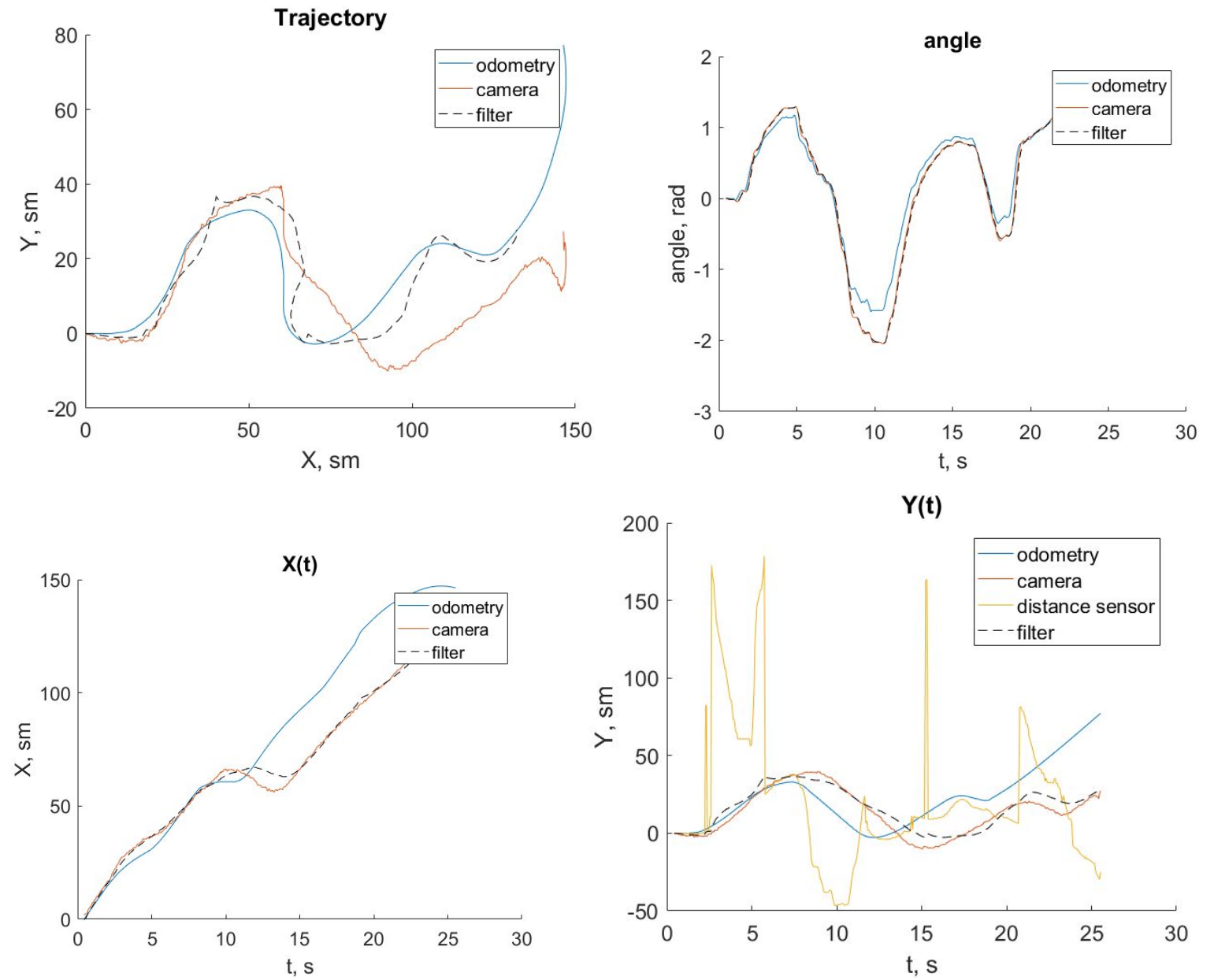
Let's consider 2 possible variants of work with odometry data. In the first case, we take the counted values $\{X, Y, \theta\}$ from the odometry. In the second case, we take the value of the velocities $\{V_x, V_y, w\}$ and apply them to the previous optimal value, in this case, $\text{SigmaOd} = 0.1$.

Results:

1 Variant.



2 Variant.



The second version of the filter produces better results because it has a more intelligent structure, namely, it applies the odometry data to the already filtered position.

The first option is more similar to the data fusion which is presented in first part.

Extended Kalman filter

For this filter, the previous model is not suitable, since it is already linear, so we will use odometric data as a model for predicting the position of the robot.

$$\hat{x}_t = f(x_{t-1}, u_t) = \begin{bmatrix} x_{t-1} \\ y_{t-1} \\ \theta_{t-1} \end{bmatrix} + \begin{bmatrix} \frac{\Delta s_r + \Delta s_l}{2} \cos \left(\theta + \frac{\Delta s_r - \Delta s_l}{2b} \right) \\ \frac{\Delta s_r + \Delta s_l}{2} \sin \theta + \frac{\Delta s_r - \Delta s_l}{2b} \\ \frac{\Delta s_r - \Delta s_l}{b} \end{bmatrix}$$

motion model

The Jacobian of that equation is equal:

$$G = \begin{bmatrix} 1 & 0 & -\sin(O + \Delta); \\ 0 & 1 & \cos(O + \Delta); \\ 0 & 0 & 1 \end{bmatrix};$$

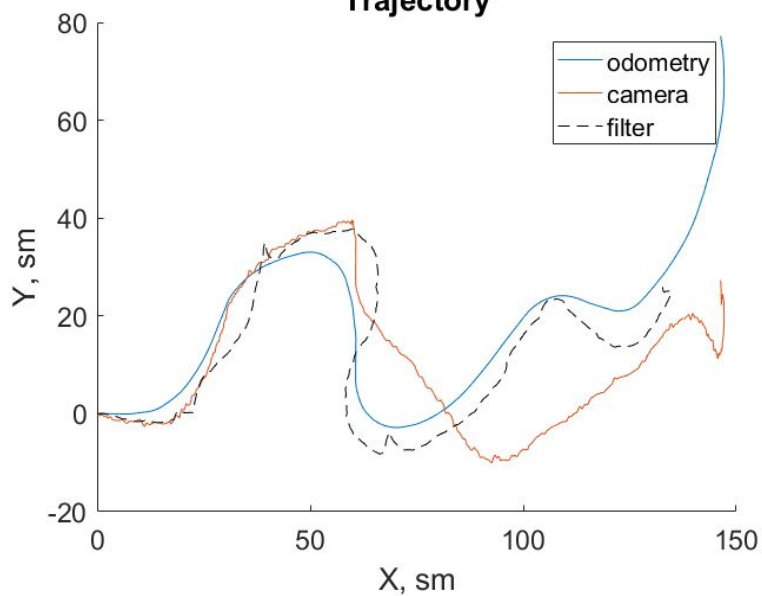
Δ - angle delta

$$H = \begin{bmatrix} 1 & 0 & 0; \\ 0 & 0 & 0; \\ 0 & 1 & 0; \\ 0 & 1 & 0; \\ 0 & 0 & 0; \\ 0 & 0 & 1; \end{bmatrix}$$

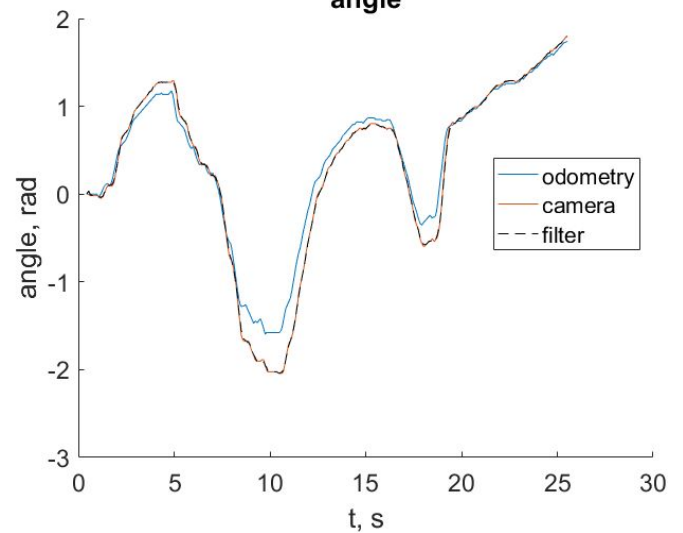
This matrix has that values, because the measurement of each sensor are directly dependent on the measured value.

Results:

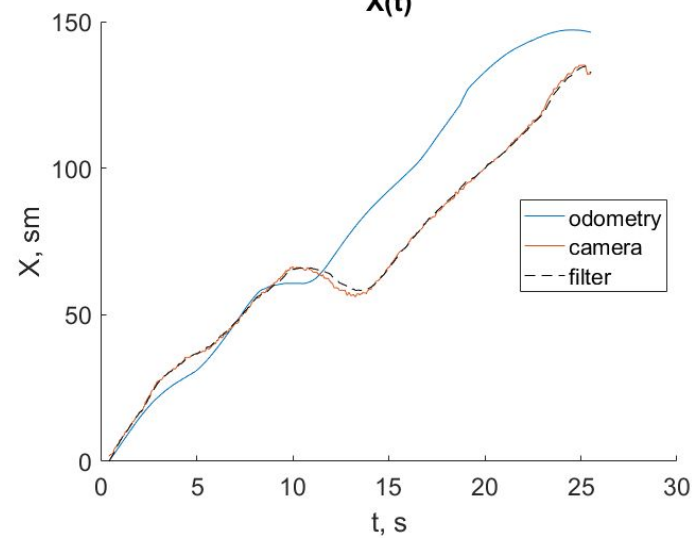
Trajectory



angle



X(t)



Y(t)

