Extended Kalman Filter Project

1. Introduction

In this project, we estimate the position of an object by means of an extended Kalman filter and sensor fusion. In particular, we combine (noisy) measurements from laser and radar sensors in order to estimate the object position.

2. Implementation

The Kalman filtering procedure consists of two steps that are carried out iteratively: prediction and update. Each time a new measurement arrives, the filter predicts the current position and velocity (using past measurements and the estimated prediction confidence) and then corrects this prediction using the current (noisy) measurement. In this sensor fusion project, we deal with data coming from two different sensors. Therefore, even though the prediction step is the same regardless of the sensor type, the update is sensor dependent. Both steps are described in more detail in the following subsections. Moreover, before the Kalman filtering procedure, the filter needs to be initialized. This initialization is decribed in the next subsection.

2.1. Initialization

After setting up the Kalman filter (noise and measurements covariance matrices, state transition function, etc.) we have to initialize the state (i.e. position and velocity) of the Kalman filter after the first measurement arrives. Since there is no prior information available, the state is initialized to the received measurement itself. However, note that the radar senses the world in polar coordinates so if the first measurement comes from the radar sensor it has to be converted to Cartesian coordinates (which is the basis we are working on).

2.2. Prediction

The prediction step assumes that the motion is linear, i.e.

$$\vec{p}_n = \vec{p}_{n-1} + (t_n - t_{n-1})\vec{v}_{n-1}$$

where p denotes the position, t corresponds to the time stamp, v is velocity and n is the index of the current measurement. This equation is used to update the next state. In addition, the process covariance matrix has to be updated as well. This matrix represents the confidence of how accurate the prediction is. The confidence shrinks (covariance increases) the higher the time interval between the current and the previous state. This is due to the fact that the assumption of motion linearity (see equation above) is a good approximation for small intervals of time and becomes less accurate if this interval grows.

2.3. Update

Unlike the prediction step, the update step (which also includes updating the process covariance matrix) varies according to the type of measurement (laser or radar). For laser measurement, we employ the classic Kalman filter update step. For the radar measurements, the extended Kalman filter update step is applied since the mapping between the measurement and the state space is not linear. Therefore, we linearize this matrix around the measurement point by applying the first order Taylor's expansion (which translates in substituting the H matrix by the corresponding Jacobian).

To sum up, before the actual update, we have to set the mapping matrix (H) and measurement covariance matrix (R) according to the type of measurement (laser or radar) we are currently dealing with.

3. Results

We have evaluated the implemented Kalman filter on Dataset 1. The evolution of RMSE for both position and speed are shown in Fig. 1. The final RMSE values are (0.097, 0.085) for $(x,\ y)$ and (0.45, 0.44) for $(v_x,\ v_y)$.

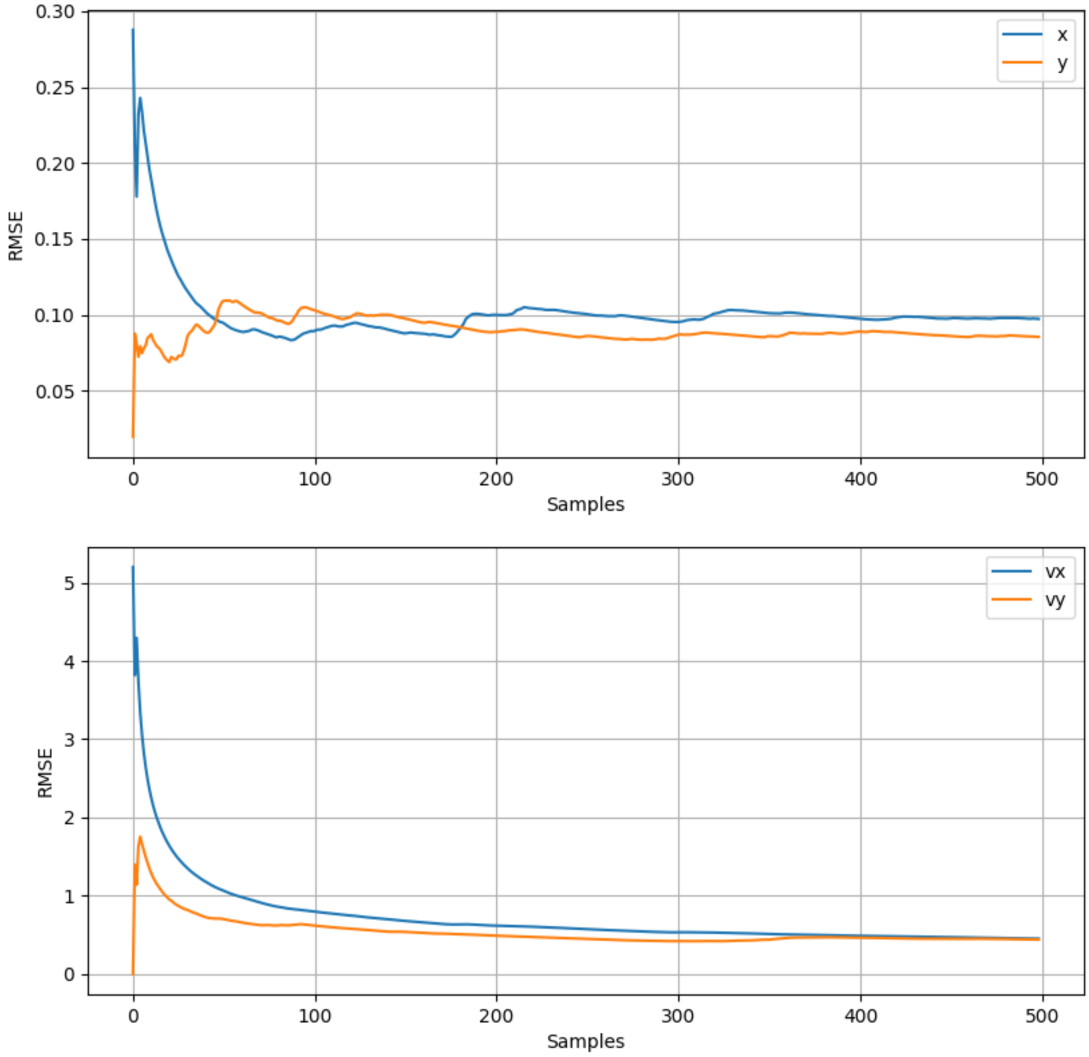

Figure 1: Evolution of RMSE for position and velocity using sensor fusion with extended Kalman filter.

It can be observed that for both position and velocity the error is decreasing and then stabilizes around the values reported above. The error cannot be reduced to zero since measurement errors are always present (even though their influence is minimized by Kalman filter). It is also observed that that the first measurement in y-axis has been much more accurate that in the x-axis. However, this is just a coincidence as also demonstrated by the later evolution of RMSE in both axis.

We have also performed the tests using laser/radar data only. In the case of laser, the resulting RMSE values are (0.18, 0.15) for (x, y) and (0.61, 0.49) for (v_x, v_y). For radar data only, the resulting RMSE values are (0.22, 0.34) for (x, y) and (0.52, 0.70) for (v_x, v_y). As expected, laser data yield lower RMSE than radar since the measurements are more accurate (as observed from the measurement covariance matrices R). On the other hand, both simulations lead to higher RMSE than the fusion of the two sensors. This is due to two main reasons:

1. When using one of the sensors only, the time difference between two measurements is higher so the prediction step is more noisy.
2. Using two sources of noisy information yields measurements whose noise is always lower than the noise of any of the two sources separately.

Finally, the comparison of the results obtained by fusing laser and radar data, by using laser data only and by using radar data only is shown in Fig. 2.

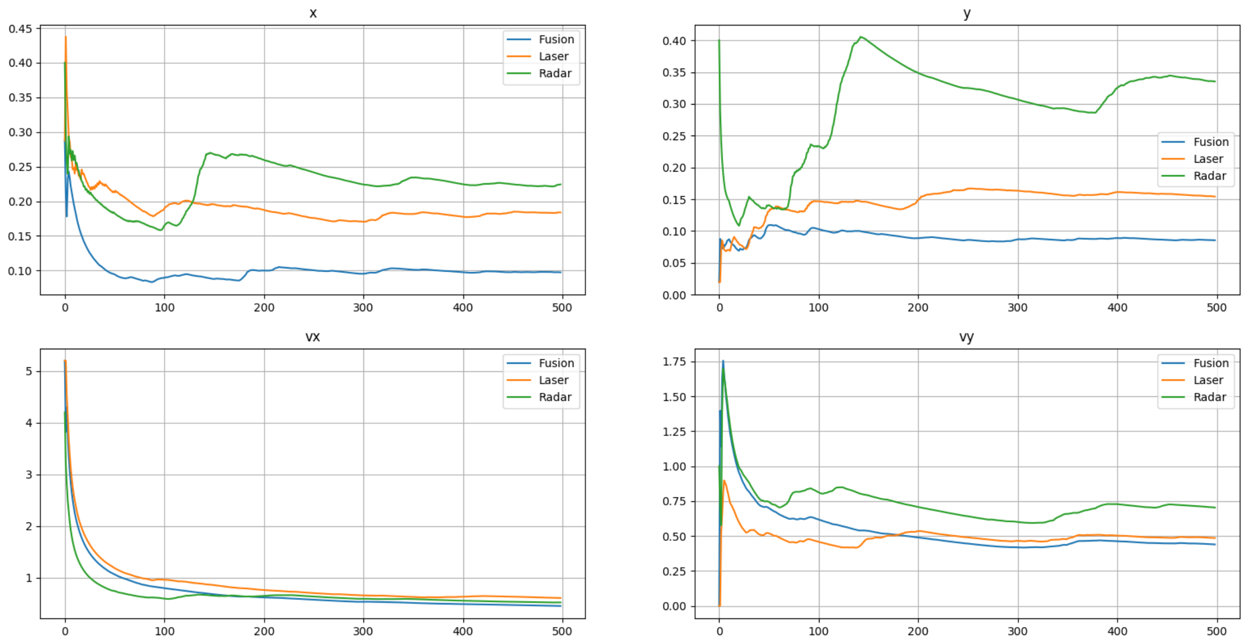

Figure 2: Comparison of RMSE obtained by sensor fusion and by using each sensor separately.