MotorAI

Technical Challenge

Student name: *Vardeep Singh Sandhu*

Due date: *January 11th, 2023*

Question 1

Give some advantages and disadvantages of RADAR over LiDAR.

Answer. **Advantages:** RADAR has several advantages over LiDAR for autonomous driving applications:

1. RADAR is less affected by weather conditions: RADARs utilize electromagnetic radio waves which operate on larger wavelengths which can penetrate through rain, snow, fog, and dust, whereas LiDAR is significantly affected by these weather conditions.
2. RADAR is less expensive: RADAR sensors are cost-effective active sensors. Additionally, they have been present in the automotive industry for the past two dacades for its applications in automatic cruise control and blind spot detection. LiDAR systems are significantly more expensive than RADAR systems, making them less practical for widespread adoption.
3. RADAR provides additional valuable information: In addition to the location information RADAR sensors also record the Doppler velocity and reflectivity of objects present in the surroundings from the received signal. These additional features, especially the Doppler velocity, give us information on the radial velocity of the objects in the scene and provide unique information for different applications.
4. RADAR has a longer range: RADAR systems can detect objects at longer distances compared to LiDAR, making them more suitable for detecting objects at a distance.
5. RADAR is more robust: LiDAR systems are more sensitive to vibrations and movements, whereas RADAR systems are more robust and can operate reliably even in rough conditions.

Disadvantages: However, there are also different disadvantages of RADAR over LiDAR:

1. RADAR has lower resolution: LiDAR systems have much higher resolution compared to RADAR and it is quite a dense representation of the environment, which allows them to create a more detailed and accurate 3D map of the environment.

2. RADAR is less accurate: LiDAR systems are more accurate at detecting the position and shape of objects, whereas RADAR can sometimes struggle with these tasks.

3. LiDAR is better at detecting small objects: LiDAR can detect smaller objects than RADAR, making it better at detecting pedestrians and small obstacles.

4. LiDAR is better at detecting fast-moving objects: LiDAR systems have a faster update rate compared to RADAR, which makes them better at detecting and tracking fast-moving objects.

5. LiDAR is better at detecting objects at close range: LiDAR systems have a shorter minimum detection range compared to RADAR, making them better at detecting objects that are close to the vehicle.

Question 2

Late fusion task.

Answer. In our task, we utilized the Kalman Filter which is a mathematical algorithm that is widely used in control systems and engineering to estimate the state of a system based on a series of noisy measurements.

In our task, we observe a single vehicle moving in 2D with two sensors, RADAR and LiDAR. The RADAR data outputs x, y, v_x, v_y which is the position and the velocity information of the vehicle in 2D. Whereas, the LiDAR sensor outputs x, y which is just the position information of the vehicle in 2D. Thus at an instant of time, we are given RADAR and LiDAR measurements of a vehicle.

Now, the Kalman Filter algorithm works in two steps, namely:

Prediction Step where the previous state estimate and the system dynamics are used to predict the system's current state. In our case, since we are given the velocity information of the vehicle we design our system dynamics linearly by just using the following equation:

$$x_{t+1} = \underbrace{x_t + v_t \times \Delta t}_{\mathrm{I}} + \underbrace{\frac{1}{2} a_t \times \Delta t^2}_{\mathrm{II}} \tag{1}$$

where, x_{t+1} is the new position, x_t is the position information, v_t is the velocity and a_t is the acceleration information at time t. In matrix form this can be given as:

$$\hat{x}_{t+1} = \mathbf{A} \times x_t,$$
$$\mathbf{P}_{t+1} = \mathbf{A} \times \mathbf{P}_t \times \mathbf{A}^T + \mathbf{Q},$$

where, the matrix $\mathbf{A}$ is the state transition matrix which in our case uses the velocity and pose information of the current time to predict the next state, $\mathbf{P}_t$ represents the predicted covariance matrix for the state estimate at time t.

It can be seen that the **I** part of the equation 1 is known and is represented in matrix **A** but since part **II** of the equation is unknown i.e. the acceleration is unknown it is considered as a gaussian random variable and is included in the matrix **Q** which is the process noise.

Update Step utilizes the new measurement from the LiDAR to update the state estimate. The mathematical equation for this step is given below:

$$\begin{aligned}
Y_{t+1} &= Z_{t+1} - \mathbf{H} \times \hat{x}_{t+1}, \\
\mathbf{S}_{t+1} &= \mathbf{H} \times \mathbf{P}_{t+1} H^T + \mathbf{R}, \\
\mathbf{K}_{t+1} &= \mathbf{P}_{t+1} \times H^T \times \mathbf{S}_{t+1}^{-1}, \\
x_{t+1} &= \hat{x}_{t+1} + \mathbf{K}_{t+1} \times Y_{t+1}, \\
\mathbf{P}_{t+1} &= (\mathbf{I} - \mathbf{K}_{t+1} \times \mathbf{H}) \times \mathbf{P}_{t+1},
\end{aligned}$$

where, Z_{t+1} is the LiDAR measurement at time $t+1$, Y_{t+1} is the measurement residuals at $t+1$, $\mathbf{K}_{t+1}$ is the Kalman Gain at time $t+1$, $\mathbf{H}$ is the matrix that maps the predicted state $\hat{x}_{t+1}$ to the measurements Z_{t+1}, $\mathbf{R}$ is the measurement noise covariance matrix, x_{t+1} is the new state for time $t+1$.

The Kalman filter repeats these prediction and update steps at each time step to produce a sequence of state estimates. To start the algorithm we initialize the state with x_0 which is the first RADAR measurement, we additionally also initialize the matrix P_t which is the covariance matrix for the state estimate. These initializations play a critical role in the overall performance of the algorithm.

Question 3

Please provide the reasoning behind the filter you selected. Are there some other filters as well, which could have been selected?

Answer. There are several sensor fusion algorithms like the extended Kalman filter (EKF), the unscented Kalman filter (UKF), and the Particle filter. These different algorithms are designed to handle systems with nonlinear dynamics or non-Gaussian noise distributions, which may be more common in robotics applications. But for our task, since the system dynamics were linear i.e. in our prediction step we could obtain the new state using a simple linear motion model given below:

$$x_{t+1} = x_t + v_t \times \Delta t + \frac{1}{2} a_t \times \Delta t^2,$$

where, x_t is the current state, v_t is the current velocity and a_t is the acceleration at time t and the next state at time $t+1$ can be estimated in a linear manner. Thus, given linear system dynamics and gaussian noise, the most appropriate choice was the Kalman filter.

If the system dynamics were non-linear i.e. the RADAR measurements were in polar coordinates then we could have utilized EKF or UKF where first from the non-linear system equations a linear motion model is estimated and then this estimated linear motion model is utilized in the same manner as Kalman filter to obtain results.