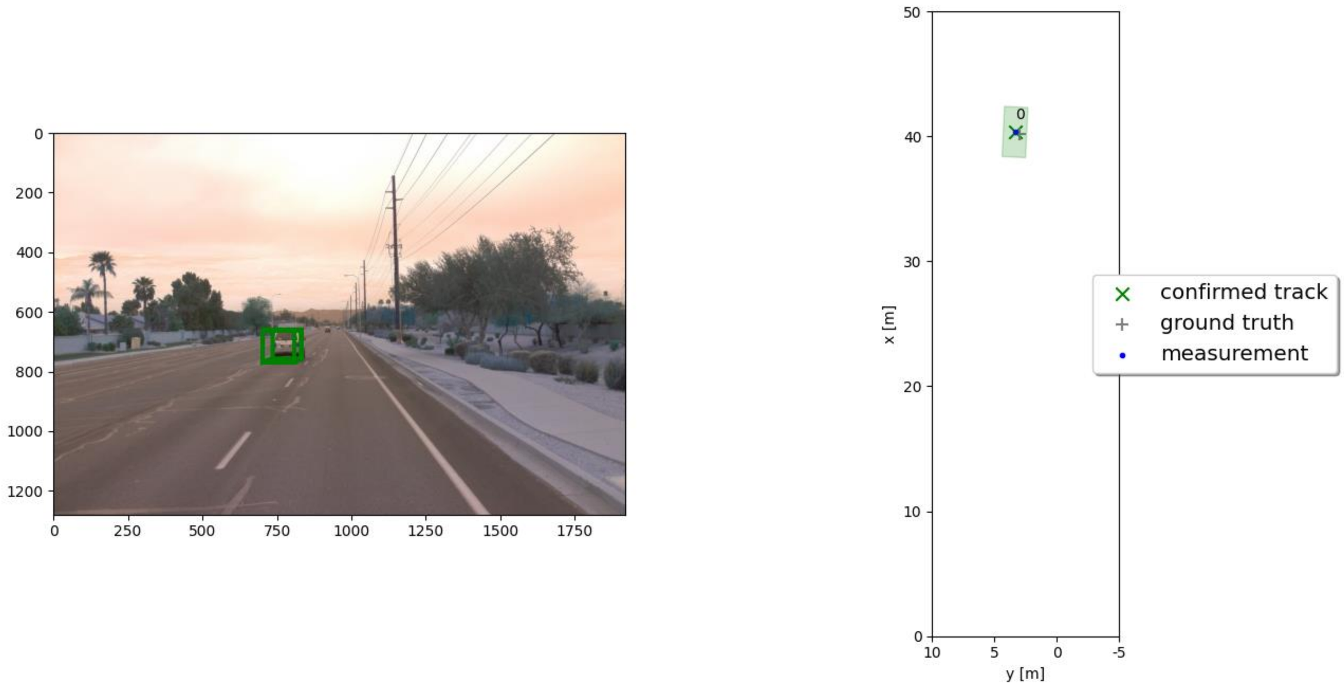
SENSOR FUSION AND OBJECT TRACKING

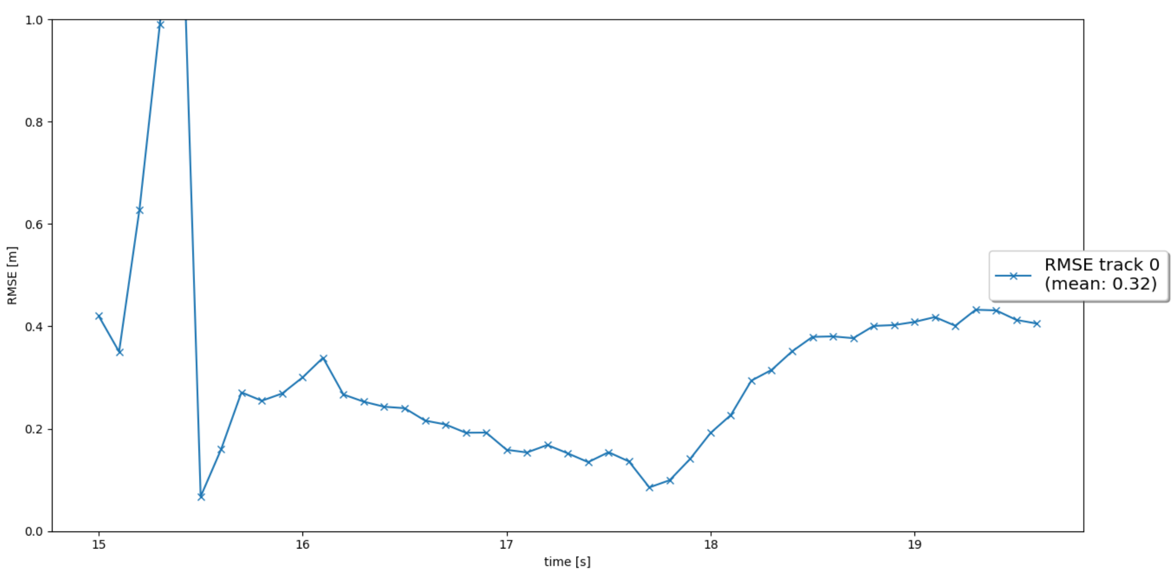
RECAP

Project Step 1

Step 1 deals with the implementation of an Extended Kalman Filter (EKF) for tracking a simple vehicle based on lidar sensor data. To solve this problem, the predict() and update() functions of the file "filter.py" are worked. In addition, the functions for the calculation of F(), Q(), gamma() and S() are developed. Where F() corresponds to a 3D constant velocity process model, Q() is the process noise covariance, gamma() is the residual, and S() is the covariance matrix. Once again, after completing the update step, the resulting state vector, x, and covariance matrix, P are calculated. The result obtained is a Root Mean Square Error (RMSE) plot showing an average RMSE of 0.32 as presented in Fig. 1b.



(a)



(b)

Fig. 1. Results from Step 1: (a) Tracking a single-target base on lidar data (b) RMSE tracking index.

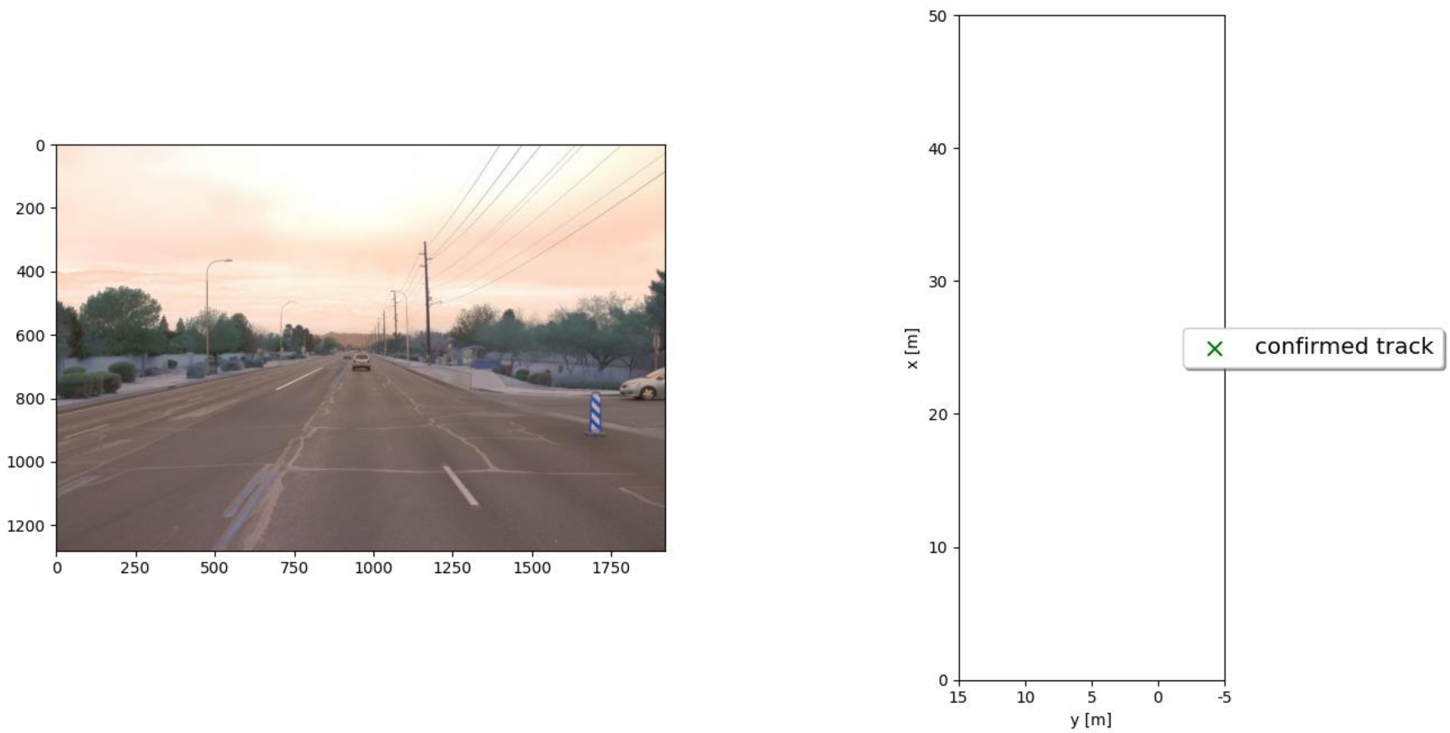
Project Step 2

In Step 2 of the final project, the track management to initialize and delete tracks, set a track state and a track score are implemented. In this task two functions are implemented, they are manage_tracks() and handle_updated_track(). The manage_tracks() function performs the following tasks:

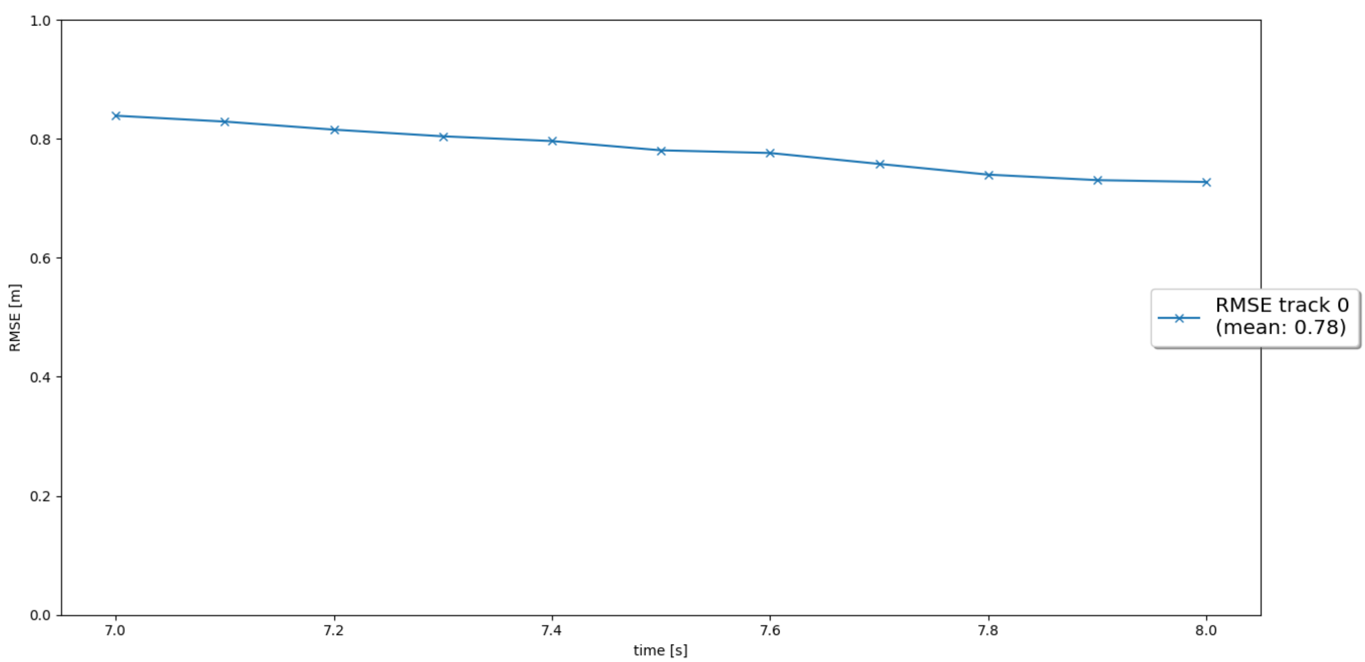
- Decrease the track score for unassigned tracks.
- Delete tracks if the score is too low or P is too big.

The handle_updated_track() function performs the following tasks:

- Increase the track score for the input track.
- Set the track state to 'tentative' or 'confirmed' depending on the track score.



(a)



(b)

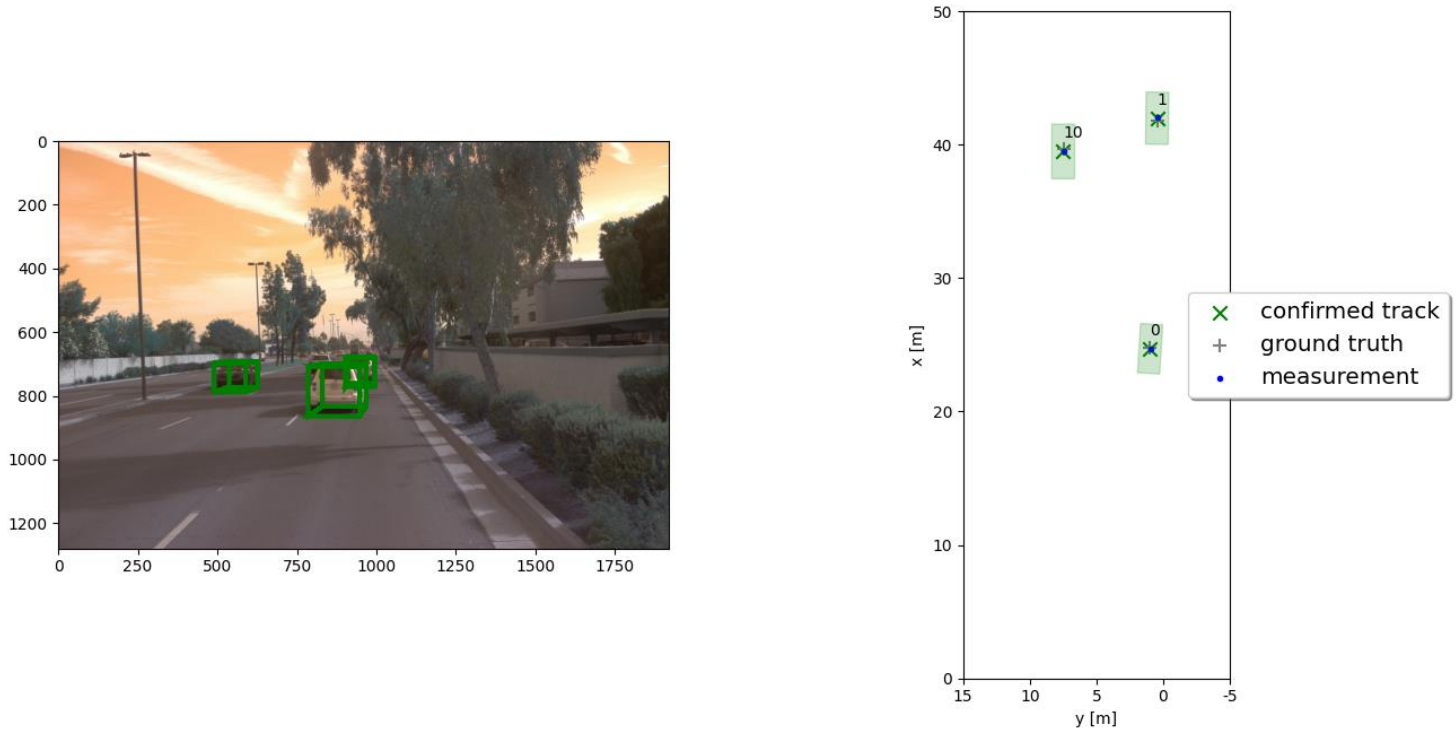
Fig. 2. Results from Step 2: (a) Tracking a single-target base on lidar data (b) RMSE tracking index.

Project Step 3

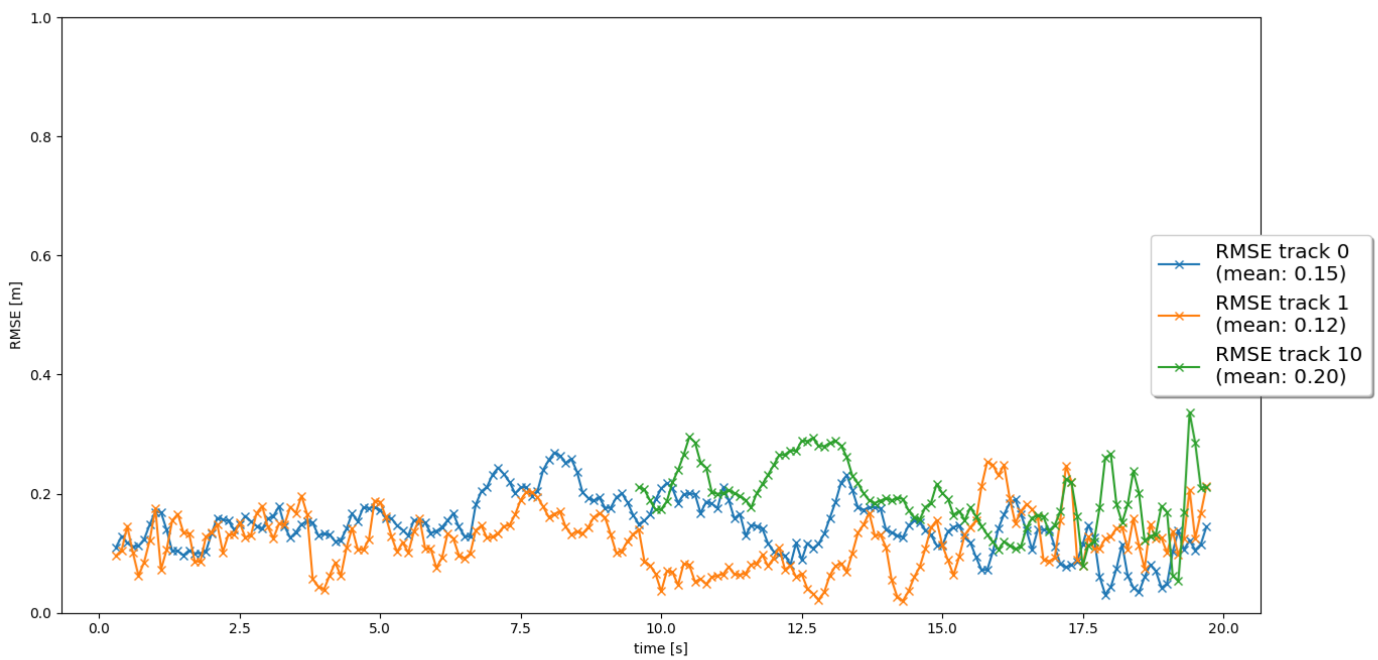
In Step 3, a single nearest neighbor data association to associate measurements to tracks is implemented. This is a multi-target tracking scenario. In this task three functions are implemented, they are associate(), gating() and get_closest_track_and_meas(). Association matrix based on Mahalanobis distances for all tracks is used.

If the minimum entry is found in the **association_matrix** the corresponding row and column are removed from the matrix. In addition, the corresponding track and measurement are removed from **unassigned_tracks** and **unassigned_meas.** There are some initialized or tentative "ghost tracks" that are removed after several frames.

In Fig. 3, the result obtained is a Root Mean Square Error (RMSE) plot showing an average RMSE of 0.15, 0.12 and 0.2 from Track 0, Track 1 and Track 10, respectively.



(a)

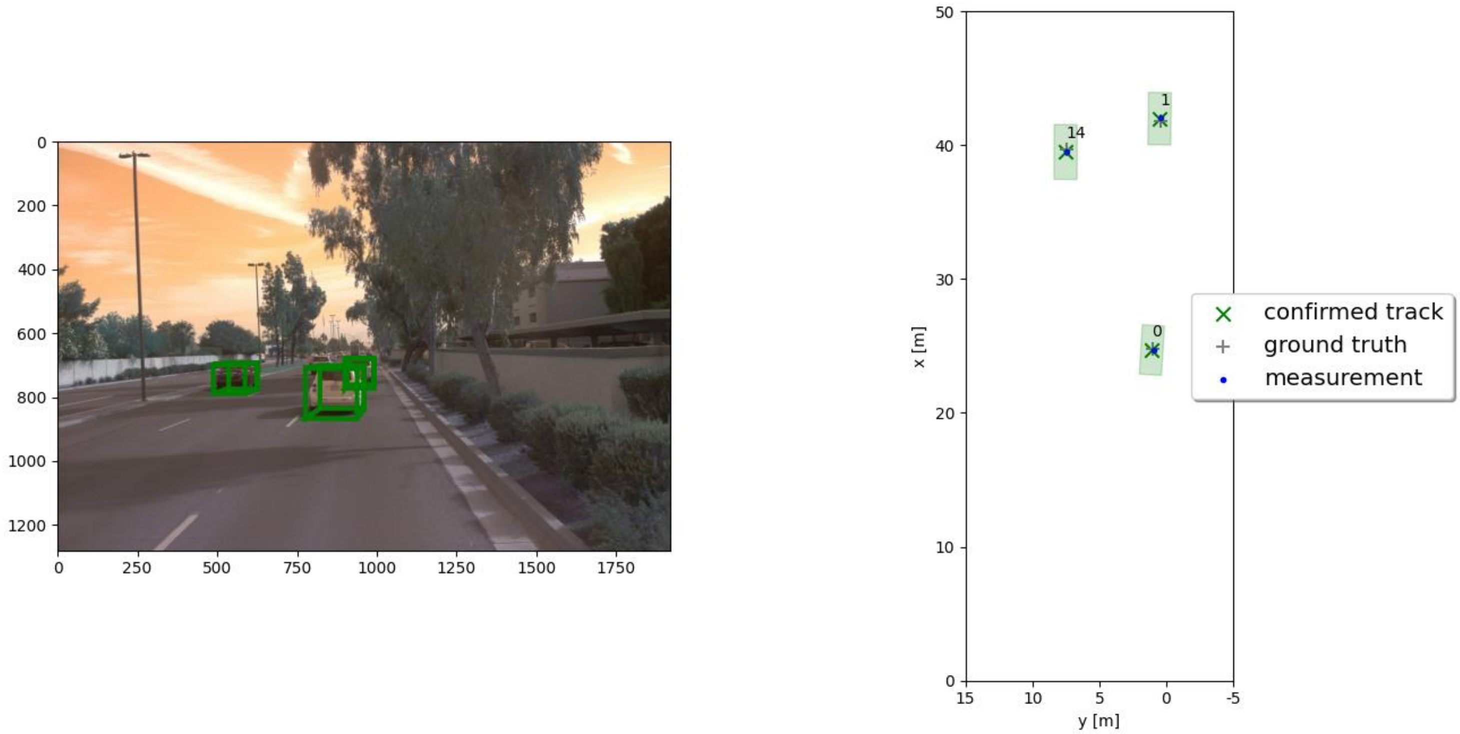


(b)

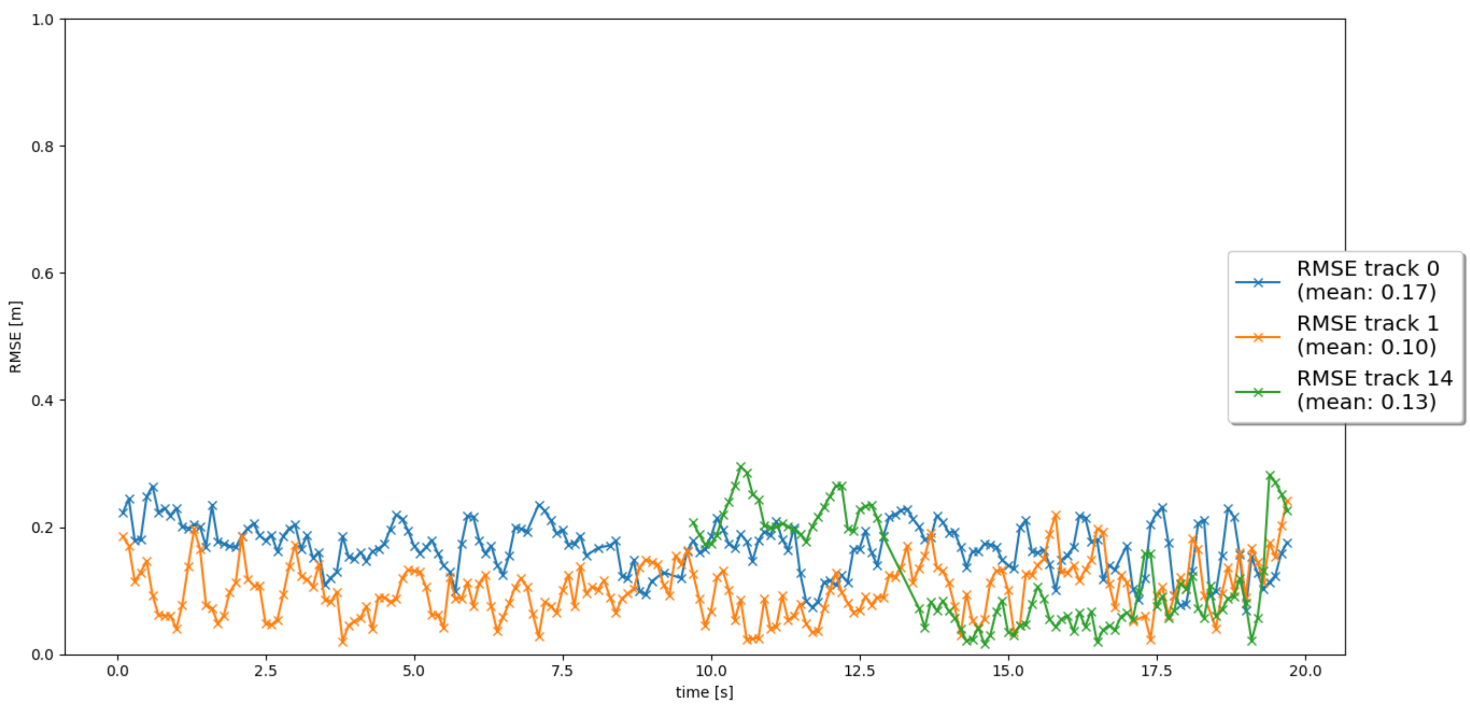
Fig. 3. Results from Step 3: (a) Tracking multi-target base on lidar data (b) RMSE tracking index.

Project Step 4

In Step 4, the nonlinear camera measurement model and linear lidar model are implemented. The sensor fusion module for camera-lidar fusion is completed. There are no confirmed ghosts and loss tracks. In Fig. 4, the results obtained is a Root Mean Square Error (RMSE) plot showing an average RMSE of 0.17, 0.10 and 0.13 from Track 0, Track 1 and Track 10, respectively.



(a)



(b)

Fig. 4. Results from Step 4: (a) Tracking multi-target base on lidar data (b) RMSE tracking index.

The most difficult tasks to do in this project was the Step 1 because I was used the 'detect_objects' by error and I was getting a very high RMSE of 0.8. Another of the difficult parts was understanding the coordinate transformations and the obtaining of the covariance matrices and their discretization.

Benefits of camera-lidar fusion tracking

One of the main advantages of combining data from cameras and lidar sensors is the complementary nature of the information they provide. Thus, it can be improved in multiple aspects such as: Lidar Reflectivity Sensation, Depth Perception, Improved Accuracy, Improved Ghost Tracking, among others.
Camera-lidar fusion is a powerful technique that offers a range of benefits in the field of sensor fusion and perception for various applications. One of the primary advantages of combining data from cameras and lidar sensors is the complementary nature of the information they provide.

In summary, camera-lidar fusion is a potent strategy for improving perception in various applications, particularly in environments where objects have varying reflectivity and depth information is crucial. By leveraging the strengths of both sensors and merging their data, more accurate and reliable tracking and object recognition results can achieved, ultimately enhancing the performance of the perception systems.

Challenges that a sensor fusion system faces in real-life scenarios

The project experienced cases of erroneous detections, especially on objects such as bushes, which posed a conceptual challenge in sensor fusion and perception. It questions whether an object must be confirmed by all sensor modalities before it is considered a valid detection or whether detection by a single modality is sufficient. In some scenarios, especially during adverse weather conditions such as heavy rain or strong direct sunlight, the camera mode may be affected, leading to possible false negatives or missed detections. In these cases, other modalities such as lidar can offer more reliable data.

Unexpected situations, such as the presence of accidental obstacles on the road, can challenge the accuracy of detection by a single sensor, highlighting the importance of considering all available data sources.The decision to require confirmation from all sensor modalities or accept detections from a single modality depends on the specific application, the reliability of the sensors, and the challenges presented by adverse conditions or tricky situations. Balancing detection robustness and sensitivity in sensor fusion is a complex task that requires careful consideration of project goals and actual operating conditions.

Improve tracking results

- Use more sensor modalities such as Radar, bumper sensors, hyper-spectral sensors
- Improve the machine learning models to detect the objects
- Context specific sensor fusion (e.g. bad weather, rainy, direct light, snowy)
- In addition to the vehicle on-board sensors, communicate with intelligent infrastructure (Road side units, traffic data, etc)