carnd_t2_p2_unscented_kalman_filter

Carnd - term 2 - project 2 - unscented kalman filter

Overview

The goal of this project is to build an unscented Kalman Filter (UKF) model to process a series of sensor data provided by radar and lidar. Similar to Porject 1, Extended Kalman Filter (EKF) model, same source of radar and lidar data is used. The UKF model is conected to the same simulator via uWebSocketIO.

Project Repository

All resource are located in Udacity's project repository CarND-Unscented-Kalman-Filter-Project (https://github.com/udacity/CarND-Unscented-Kalman-Filter-Project)

Project Submission

All modified code including results are committed to my personal github page carnd-t2-p2-unscented-kalman-filter (https://github.com/chriskcheung/carnd_t2_p2_unscented_kalman_filter)

Key Files

main.cpp

establishes communication between simulator and UKF model using uWebSocketIO, and reads in data during set time interval and send sensor measurements to UKF::ProcessMeasurement() in ukp.cpp for processing

ukf.cpp

contains 4 main functions: UKF::ProcessMeasurement(), UKF::Prediction(), UKF::UpdateLidarUKF(), UKF::UpdataRadar().

UKF::ProcessMeasurement() initializes state x *and process covariance matrix P* based on sensor data stypes: radar vs lidar. After initalization, delta time and meas_package will be fed to UKF::Prediction() for corresponding sigma point generation.

UKF::Prediction() generates sigma points X *base on x* and P_. Then follow by generating augmented sigma points Xsig_aug withing adding acceleration noise std*a* and radial acceleration noise std*yawdd* to existing process covariance matrix, becoming P_aug. Then, using function h(s, noise) to transform Xsig_aug predicted sigma points, Xsig_pred. Form Xsig*pred, we applied weighted summation to its sigma points to calcalate the predicted mean x*, (xk+1|k), and predicted covariance matrix P_, (Pk+1|k).

UKF::UpdateRadar() uses state transaction function h(x) to transform Xsig_pred into predicted measurement points Zsig. From Zsig, applies weighted summation to extract predicted measurement mean, z_pred. With the weighted summation of different between Zsig_pred and *zpred, and the noise of radar equipment, we calculates measurement covariance matrix, S. Then using S, we determines cross-correlation matrix, T, and calcaulted Kalman gain matrix, Kag. With T and Kag, state x*\ and process covariance P_ is updated with the new state and covariance. At the end, Normalized Innovation Square, NIS, is calculated to verify consistence.

UKF::UpdateLidarUKF() uses the same method as UpdateRadar, but instead of using the state transition function h(x) that composes of a 3-dimensional function for rho, phi, and rhorate, the h(x) is replaced with a 2-dimensional function for px_ and py_.

tools.cpp

includes CalculateRMSE() for calculating the root means square ofthe predicted result veruse real groundtruth measurement

Implementation Challenge

Initialization

If radar measurement input if received, use the rho, phi, and rhodot measurement to update state vector x_. Otherwise, lidar measurement is straightforward to use px_ and py_ directly.

```
    float px     = cos(phi)*rho;     // calculate position of x from radian metric phi and rho
    float py     = sin(phi)*rho;     // calculate position of y from radian metric phi and rho
```

The last, update the time*us* variable with the timestamp from measurement input as all measured sensor data are processed at this time.

Prediction

Prediction applies to both Radar and Lidar the same way as so each out. No different thread is needed to decide . TOne thing to look for is DO NOT attempt to normailzed angelse at sigma point creation. Will discuss more in later parallal.

```
  // Prepare x augmented by adding noise to x vector, then calculate X au
gmented sigma points
  VectorXd x_aug(n_aug_);   // 7
  x_aug.head(n_x_) = x_;    // fill the first 5 element with x
  x_aug(5) = 0;
  x_aug(6) = 0;
  MatrixXd P_aug(n_aug_, n_aug_);  // P_aug size is 7x7
  P_aug.fill(0.0);
  P_aug.topLeftCorner(n_x_, n_x_) << P_;
  P_aug(5,5) = std_a_ * std_a_;
  P_aug(6,6) = std_yawdd_*std_yawdd_;
  MatrixXd Xsig_aug(n_aug_, 2*n_aug_+1);  //Xsig_aug size is 7x15
  MatrixXd A_aug = P_aug.llt().matrixL(); // P_aug transpose
  Xsig_aug.col(0) = x_aug;
  for (int i=0; i<n_aug_; i++){
      Xsig_aug.col(i+1)        = x_aug + sqrt(lambda_+n_aug_)*A_aug.col(i
);
      // a mistake of normalizing angle at sigma point generations. notic
e that the first angle gets
      //   normalized started at 1 instead of 0. So ends up some angles g
et normalized while some doesn't.
      //   Leaving this here as commented code for example of bad normali
zation practice.
      // normalized angle
      while(Xsig_aug(3,i+1) >  M_PI) { Xsig_aug(3,i+1) -= 2*M_PI; }
      while(Xsig_aug(3,i+1) < -M_PI) { Xsig_aug(3,i+1) += 2*M_PI; }*/

      Xsig_aug.col(i+n_aug_+1) = x_aug - sqrt(lambda_+n_aug_)*A_aug.col(i
);
      // normalized angle
      // while(Xsig_aug(3,i+n_aug_+1) >  M_PI) { Xsig_aug(3,i+n_aug_+1) -
= 2*M_PI; }
      // while(Xsig_aug(3,i+n_aug_+1) < -M_PI) { Xsig_aug(3,i+n_aug_+1) +
= 2*M_PI; }*/
}
```

Update

Update for radar and lidar are different. Kalman filter update() for Lidar is quite straight forward by using state x directly.

```
        for(int i=0; i<2*n_aug_+1; i++){
    MatrixXd Xx  = Xsig_pred_.col(i) - x_;

    // normalize angle
    while(Xx(3) >  M_PI) { Xx(3) -= 2*M_PI; }
    while(Xx(3) < -M_PI) { Xx(3) += 2*M_PI; }

    P_ += weights_(i) * Xx * Xx.transpose();
    }
    cout << "inside prediction(223)\n";
cout << "predicted x_=\n" << x_ << endl;
cout << "predicted P_=\n" << P_ << endl;
```

Normalizing Phi Angle

It is crucial to normalize phi angle in the range between pi and -pi. The explanation had been discussed previously in Project 1. Here for unscented Kalman Filter, phi angle is normailzed every time there is a subtration on the angle, normalization should take place to ensure the range of turning can only goes from 90 degree from the center (straight) to the left(-) and to the right(+). Here (https://discussions.udacity.com/t/ekf-gets-off-track/276122/19?u=drivewell)

Overly done at prediction and sigma point generation can cause incorrect results on state x *and covariance matrix P\.*

```
// normalize phi, y(1) in this case to be within -pi to pi
while(y(1) >  M_PI){ y(1) -= 2.*M_PI; }
while(y(1) < -M_PI){ y(1) += 2.*M_PI; }
```

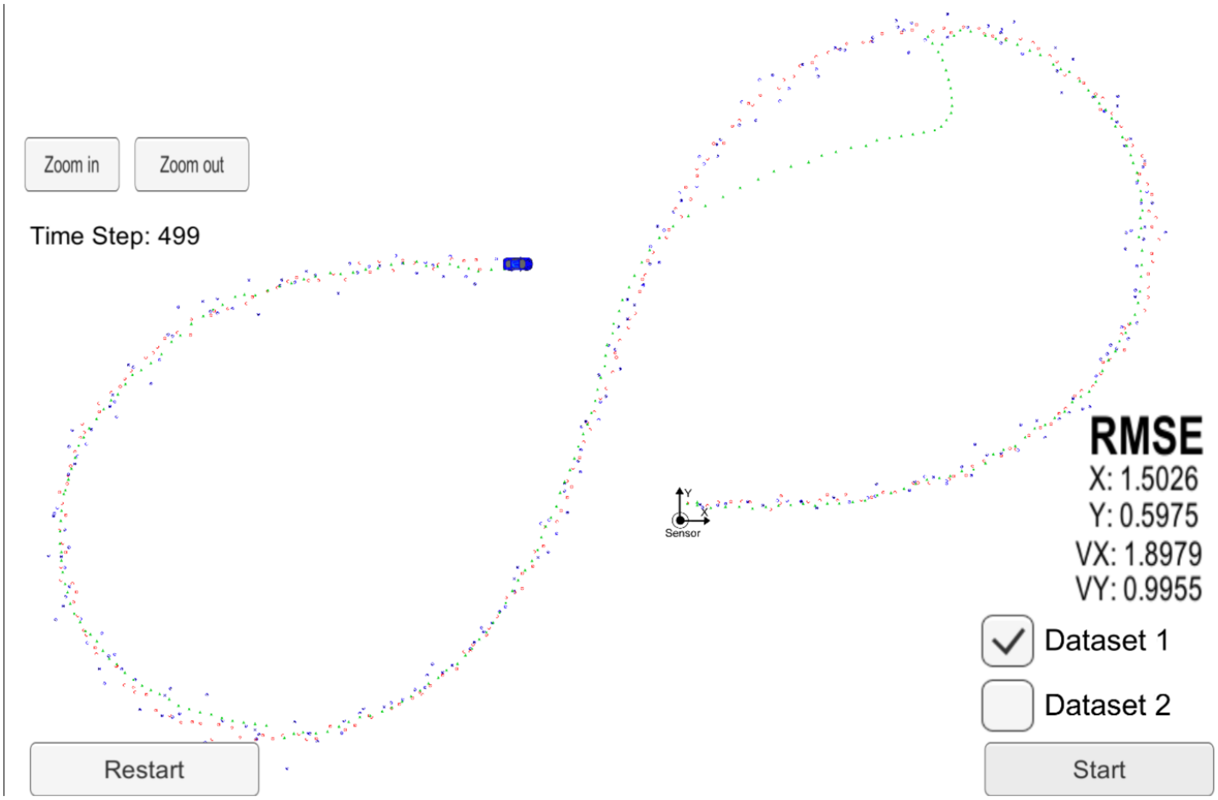
Result

Initial bring up of the code is short as I am using the old code structure from project 1. At the beginning, I got green tracker faulty mapped the estimation and pediction with bumps (off tracked) around 160 and 350 time stamps. As I observed, the calculated state x_ and covariance state matrix were increasing exponentially as raw measurement data was being processed. The problem was normalizing phi angles at sigma points generations and predicting Xaug_pred. It was a coding bug that normalization was not applied to the first sigma point phi but the rest of the sigma points, and causing an inconsistency in phi angles.

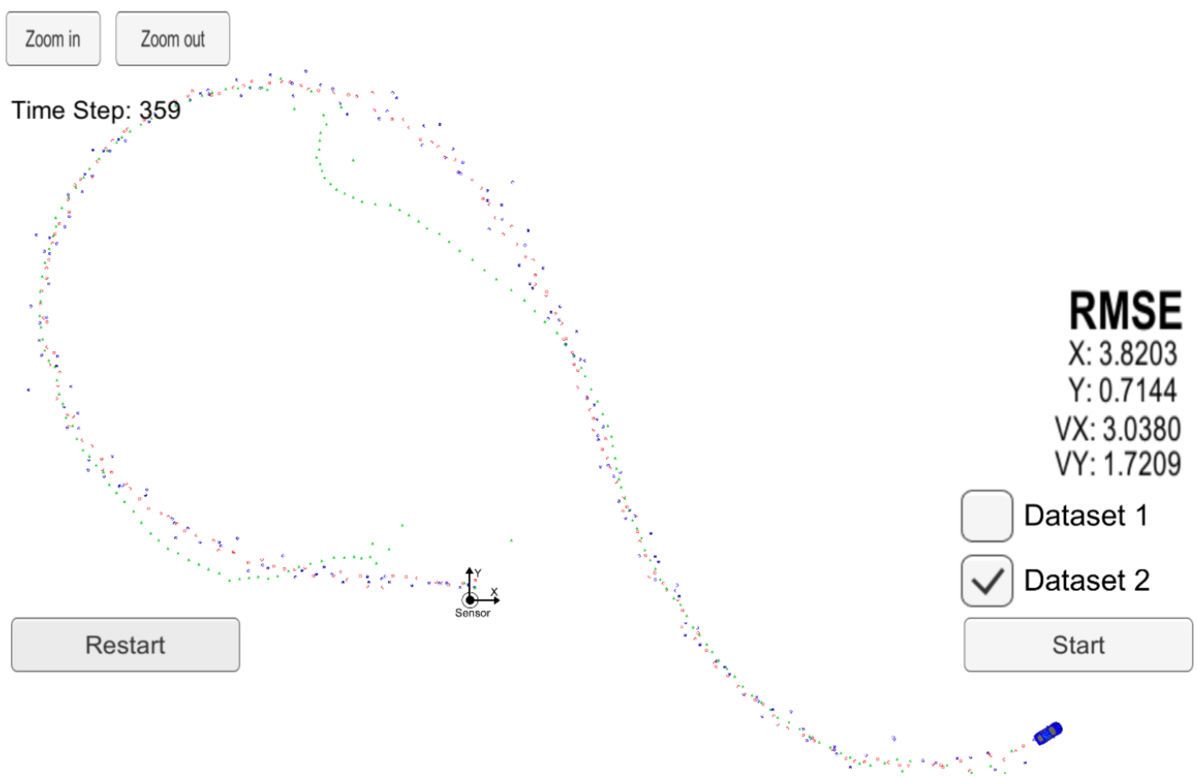
Failed attempts

Radar measurement only

dataset 1

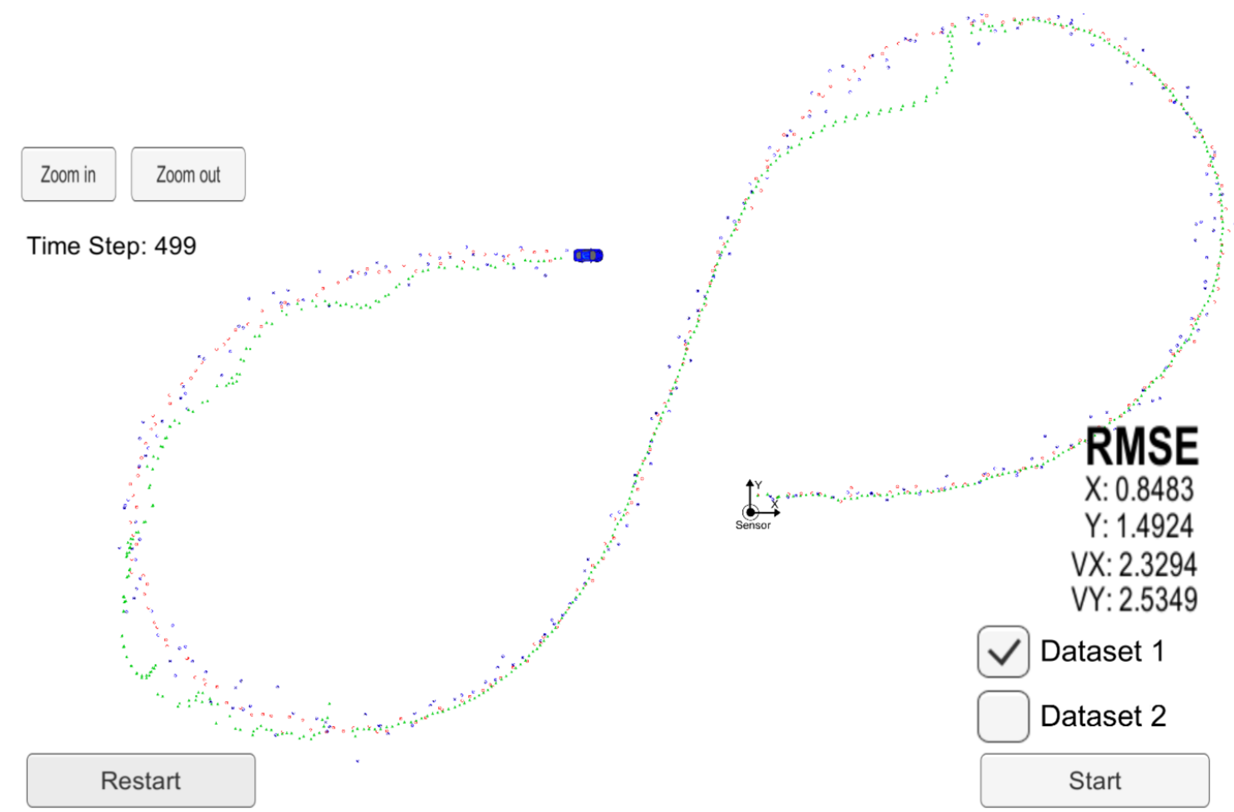


dataset 2

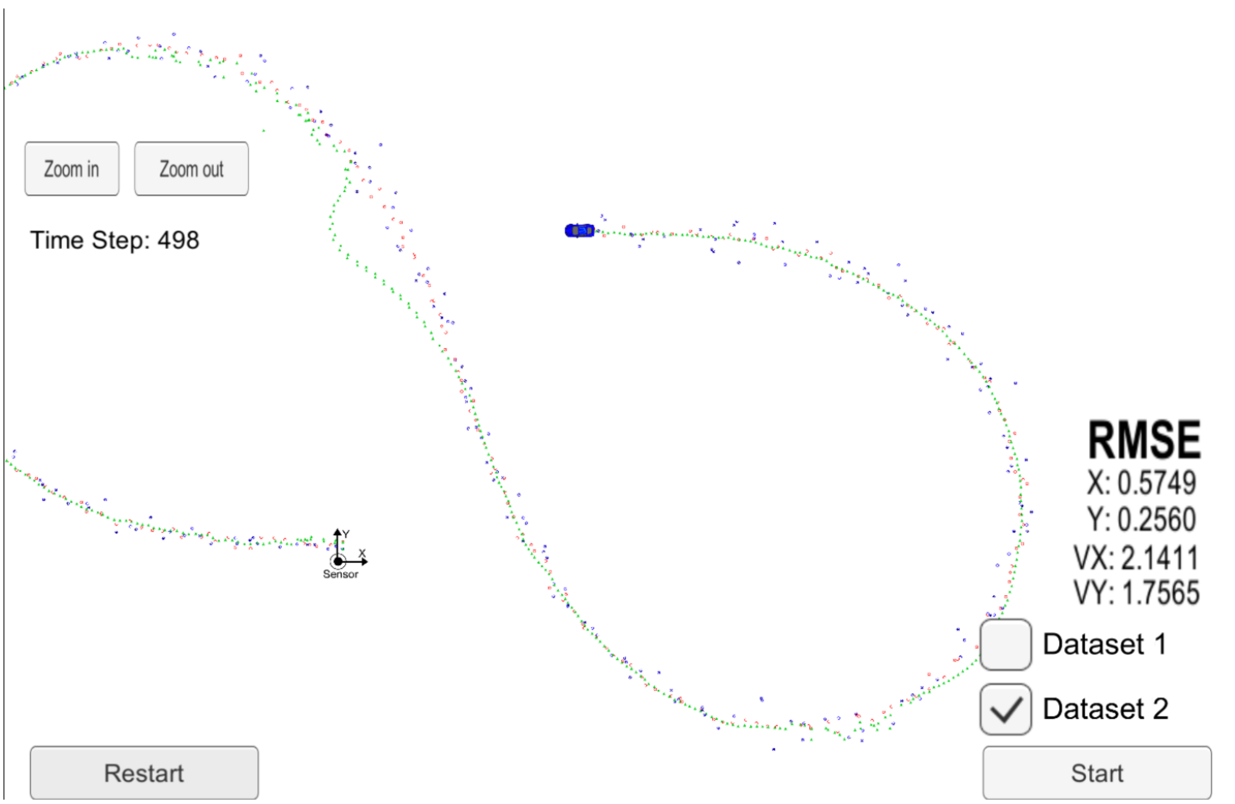


Radar and Lidar measurement

dataset 1



dataset 2



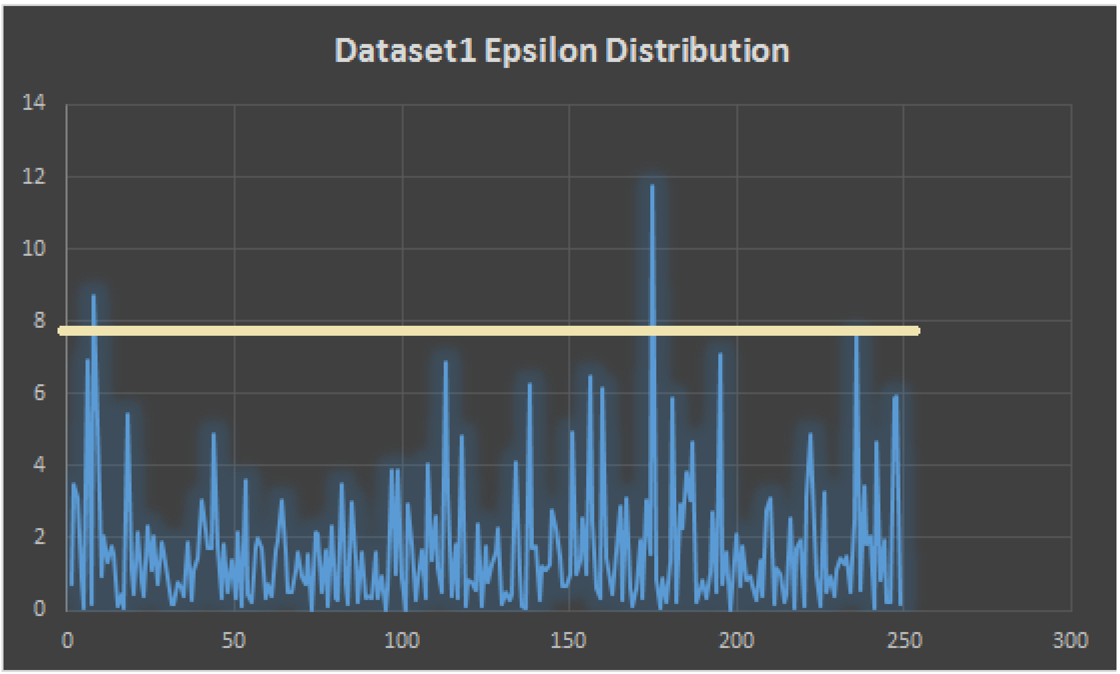
After removing the unnecessary phi normalization, the estimation (green tracker) was able to follow the tail of the car properly. Another bug discovered was caused by std_a and std*yawdd* being too larger for bicycle database. After multiple attempts to adjust the noise, I settled to the following. I also chose to initialize P_ matrix to zero except P_(0,0)=1 and P_(1,1)=1. This gave me a better result on RMSE. But sure there is room to improve.

```
std_a_ = 5.0; // .11, .10, .65, .34
std_yawdd_ = 0.7;
```

The best RMSE is close to the required rubric guideline:

```
for dataset1, (px, py, vx, vy)=(0.11, 0.10, 0.59, 0.25)
for dataset2, (px, py, vx, vy)=(0.09, 0.08, 0.48, 0.26)
```

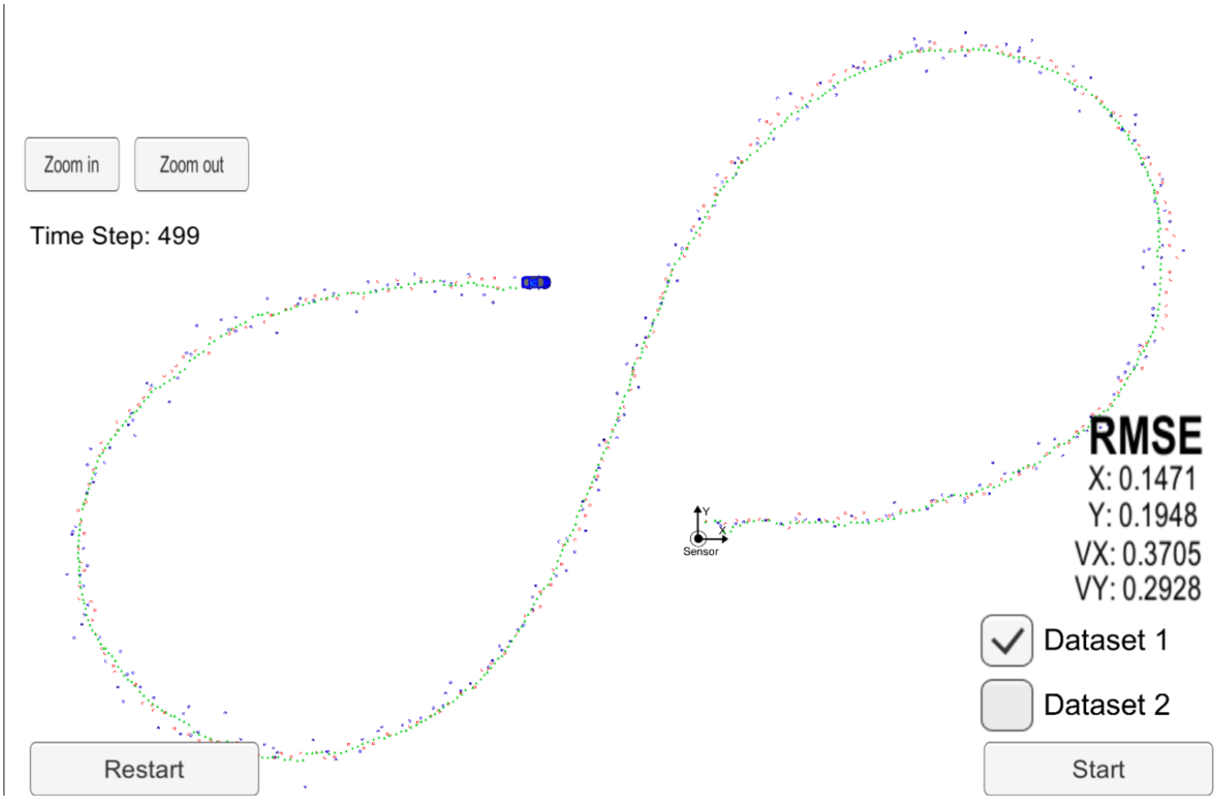
The epsilon value seems within the expectation as suggested from the lection. 95% of epsilon value are below 7.8 (shown as yellow line in chart) according to a 3 degree of freedom.



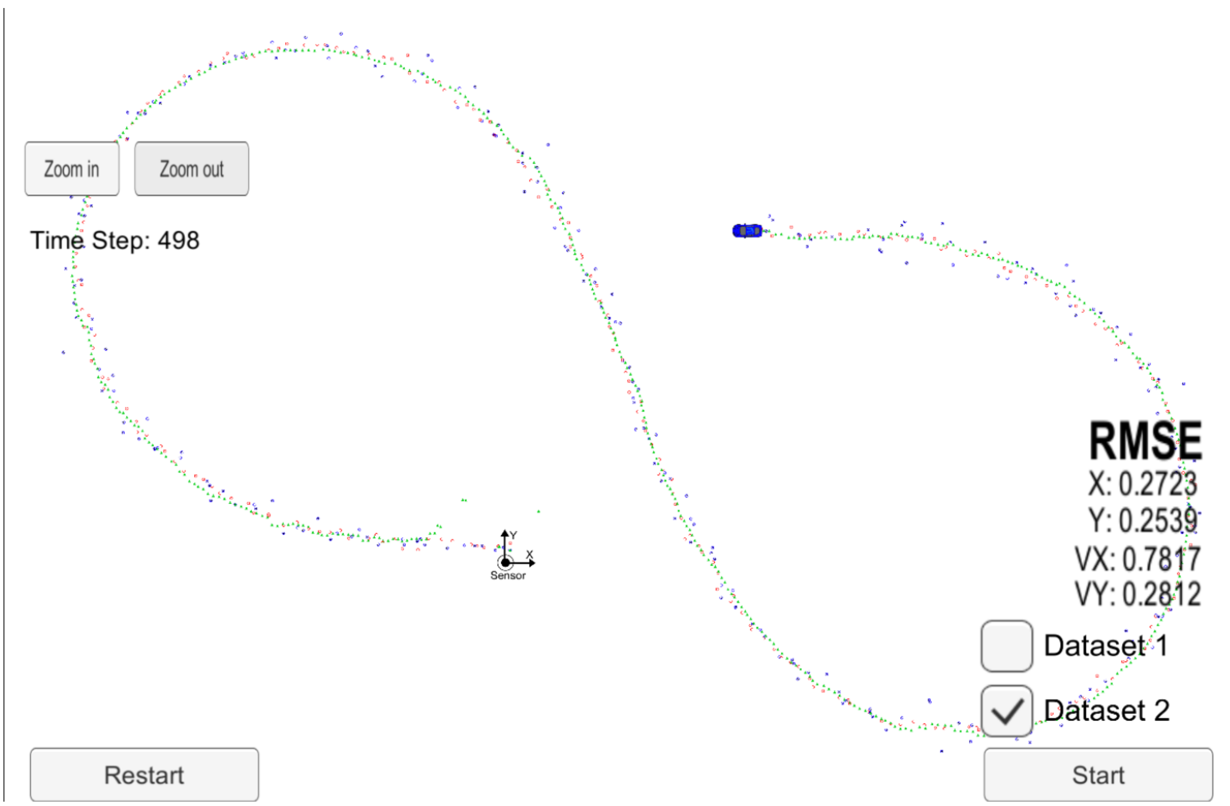
Passing cases after fixing bug

Radar measurement only

dataset 1

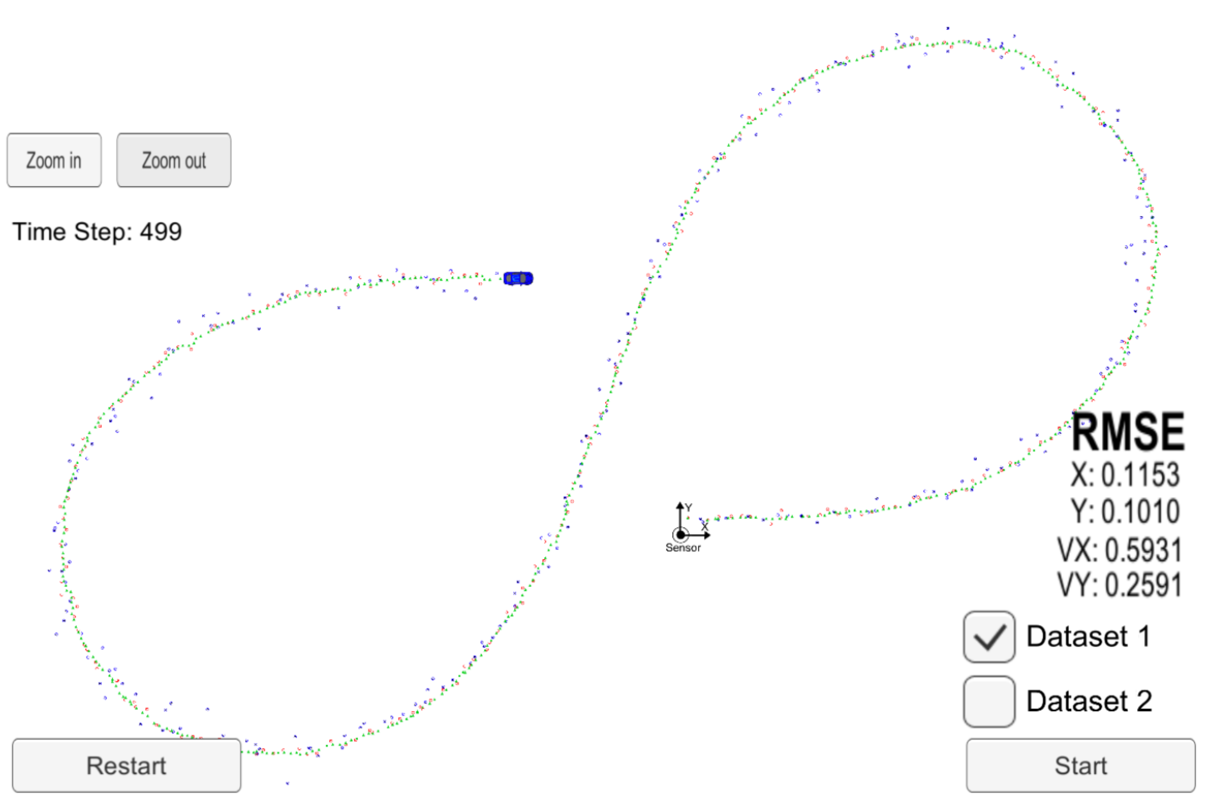


dataset 2

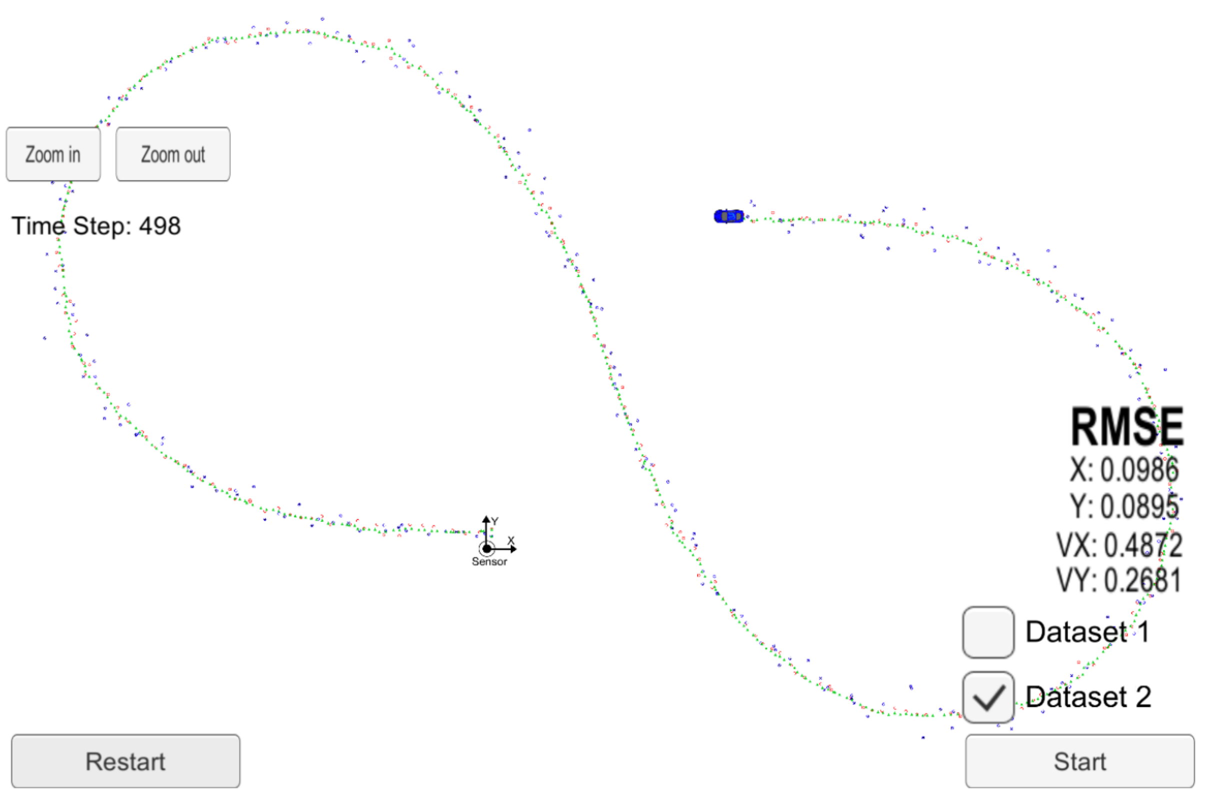


Radar and Lidar measurement

dataset 1



dataset 2



Overall, intialize bring up of this project is not diffcult as all instruction had been provided, it does require a lot time to debug the issue and tuning the acceleration and radial acceleration noices to get minimize the RMSE.

In [ ]: