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CPE470
3-3-22

Project 1: Mobile Robot Localization Using Kalman Filter

A) Explain why the Kalman Filter outperforms the individual sensor (GPS, IMU, Encoder)

The Kalman filter outperforms the individual sensors by taking a weighted average of the inputs. It combines the sensor data with the prediction to create an estimate of the robots true position that ignores noise. This is done by taking all the sensors data for a certain time, and creates a prediction based on the current position and heading, it then recursively runs through each discrete time step and compares the actual data and the prediction, and averages them to create an accurate estimation of the position.

B) Report the results to prove the concept. Give text explanations for your obtained results Below is the position data recorded from the robot circle without any noise.

Below are the graphs for the position (fig 1) and heading (fig 2) showing the data collected and the output of the Kalman filter. In the figures, the red path shows the odometry data, the black represents the gps/imu data, and the blue is the output of the Kalman filter. Looking at the path taken, the robot should have ended up exactly where it started, and the Kalman filter gives a closer approximation to the final position than the odometry and GPS data. The heading of the robot also returns to a similar position with the kalman filter estimate.

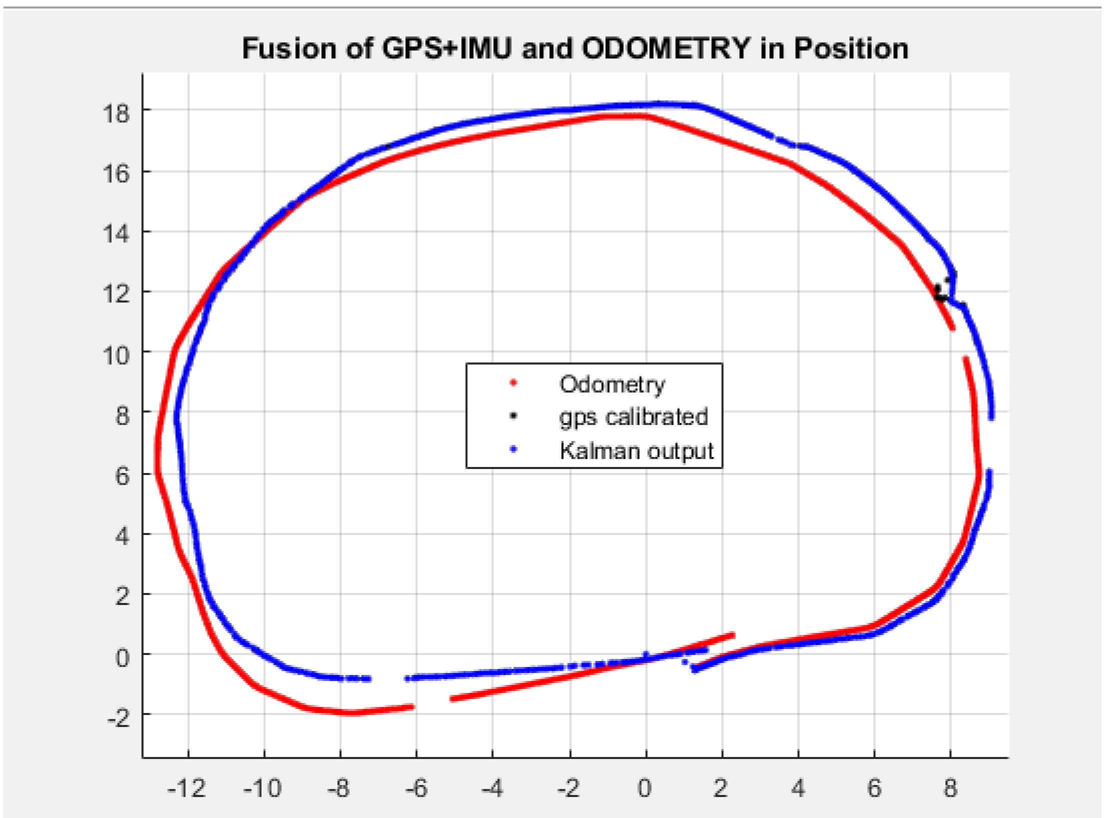

Fig. 1: Graph showing position of the robot, odometry data in red, gps data in black, and kalman filter in blue.

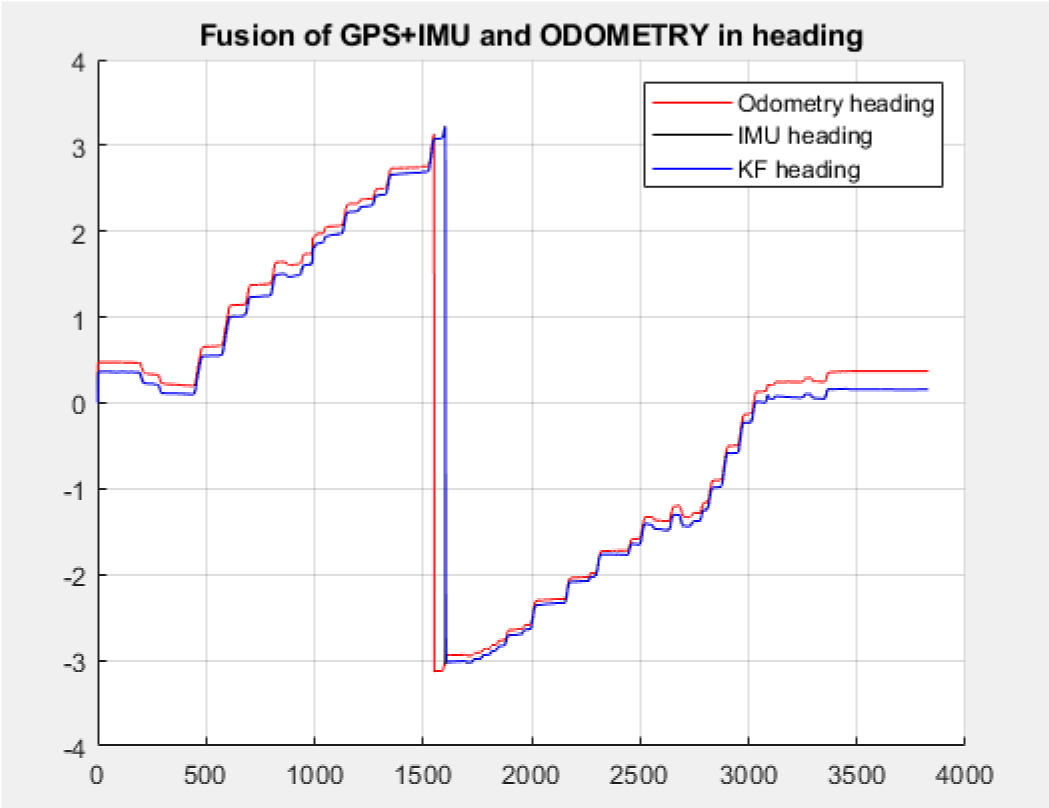

Fig. 2: Graph showing heading in radians of the robot, odometry data in red, IMU data in black, and kalman filter in blue.

C) Change the covariance of the sensor data (GPS)and check the output of the KF, then plot and explain your observation in the report.

Noise in GPS covariance (full data set).

When changing the covariance matrix to add in noise over the full data set, not much changes, this is due to the Kalman filter being able to dispose of the noise in the data and output an estimate that is more closely approximate to the physical location of the robot. Fig 3 and Fig 4 show the position and heading of the robot with the gps covariance matrix being affected by noise.

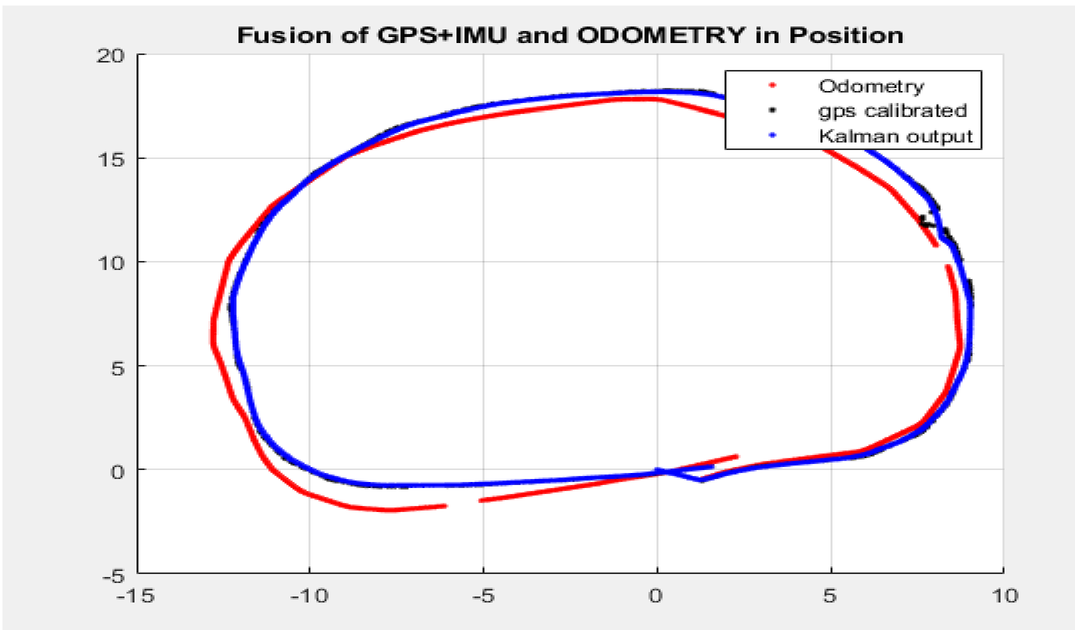

Fig. 3: Graph showing position of the robot, odometry data in red, gps data in black, and kalman filter in blue. This graph has noise in the GPS covariance matrix.

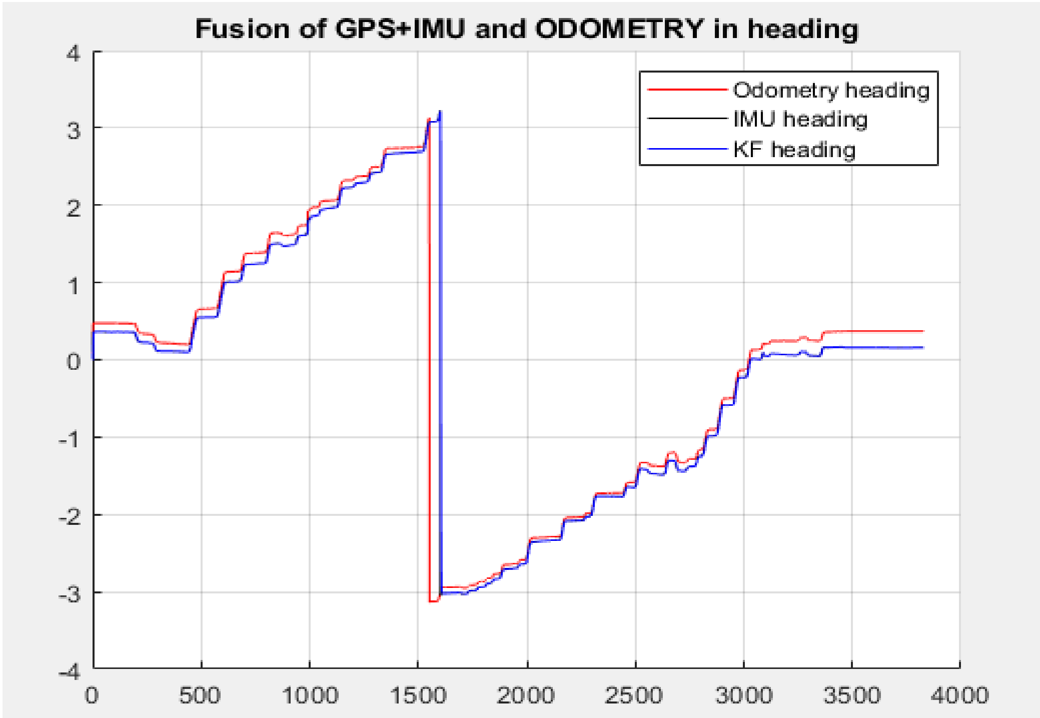

Fig. 4: Graph showing heading in radians of the robot, odometry data in red, IMU data in black, and kalman filter in blue. This graph has noise in the GPS covariance matrix.

Noise of GPS covariance data (ranges)

The noise added in this example only affects certain ranges of the data points added. The ranges that are affected are 1 through 500, 1500 through 2000, and 2500 through 3000. With these ranges, we have less noise in our system, so less of an effect is had compared to the original graphs. Fig 5 and Fig 6 show the position and heading of the robot being affected by noise during certain intervals.

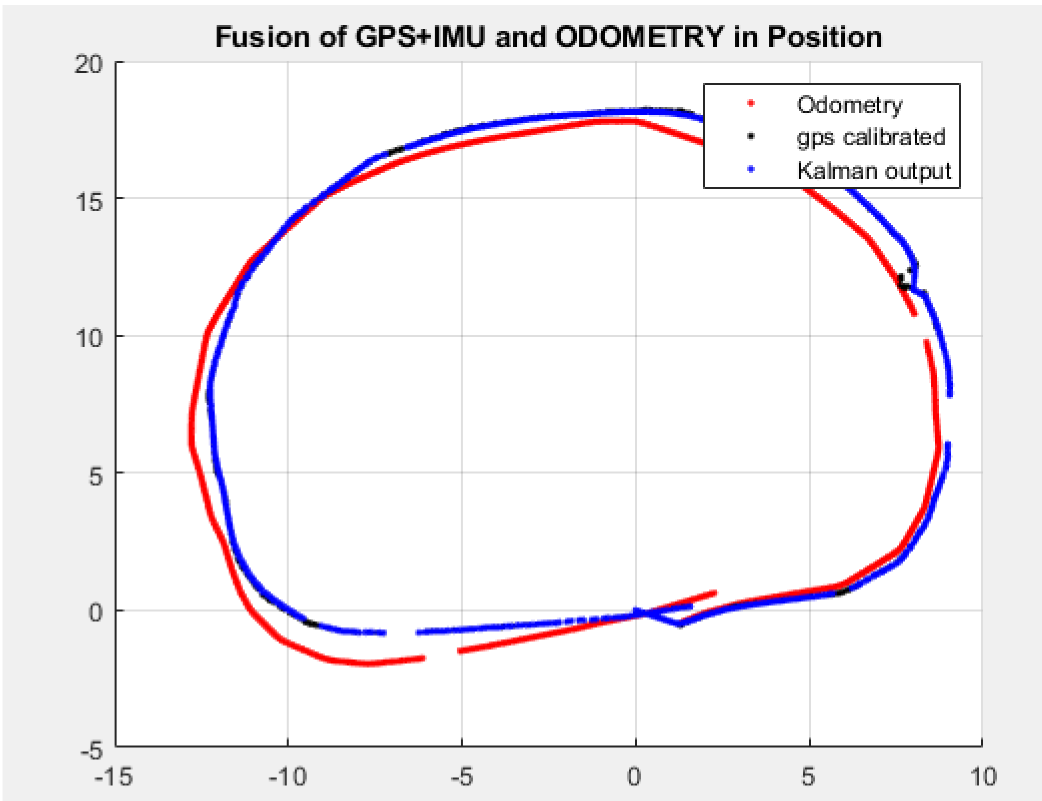

Fig. 5: Graph showing position of the robot, odometry data in red, gps data in black, and kalman filter in blue.This graph has noise in the GPS covariance matrix over intervals 1-500, 1500-2000, 2500-3000.

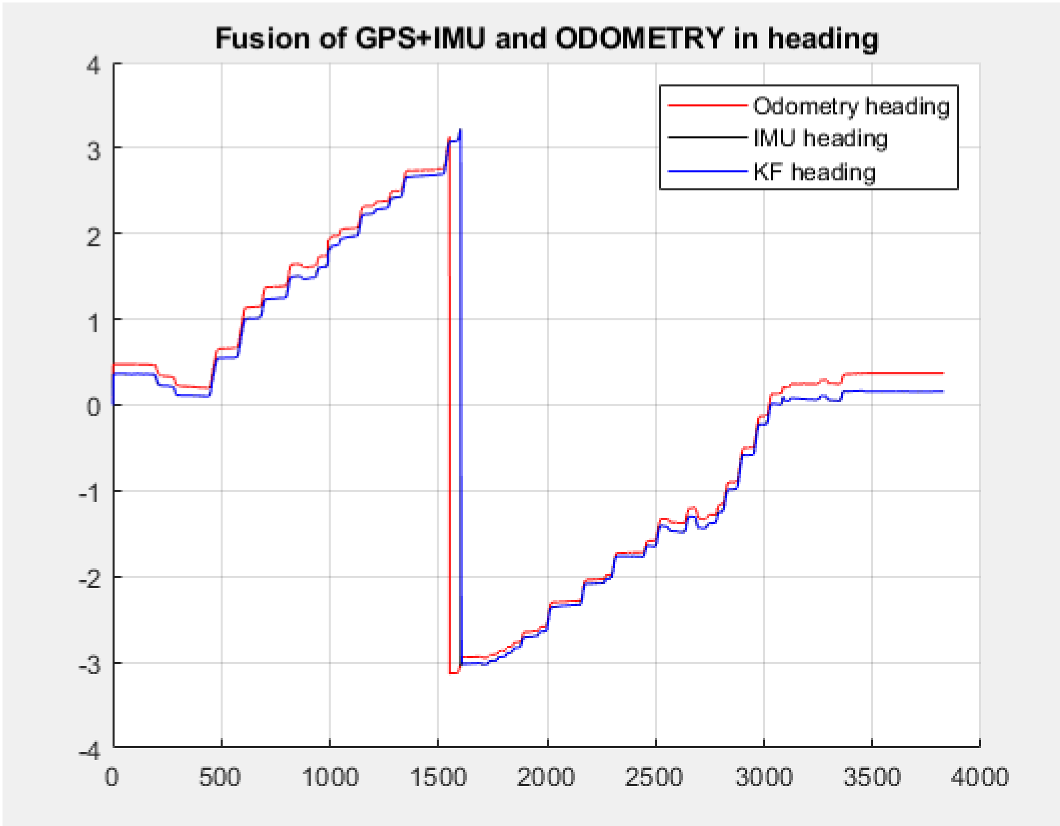

Fig. 6: Graph showing heading in radians of the robot, odometry data in red, IMU data in black, and kalman filter in blue.This graph has noise in the GPS covariance matrix over intervals 1-500, 1500-2000, 2500-3000.

D) Change the covariance of the sensor data (IMU) and check the output of the KF, then plot and explain your observation in the report.
Noise to IMU covariance (full data set)

In Fig 7 and Fig 8, we can see the effect of adding noise to the IMU covariance matrix over the entire data set. The heading of the robot is affected the most and the Kalman filter has to provide more of an adjustment. The position data of the robot does not have much of a noticeable effect.

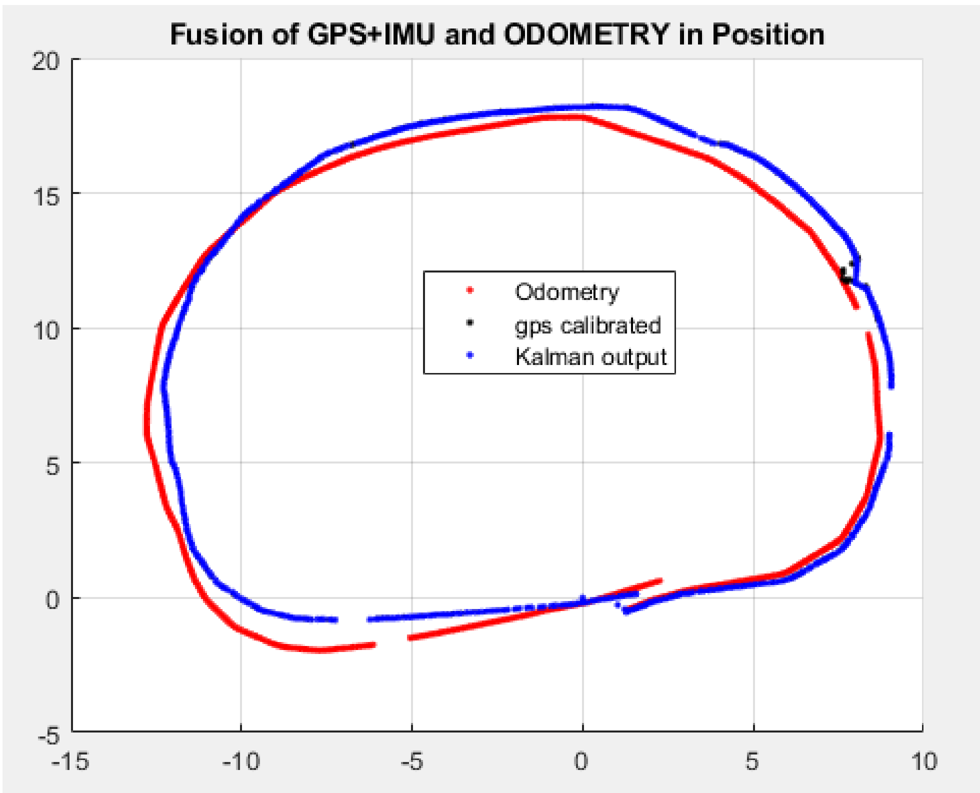

Fig. 7: Graph showing position of the robot, odometry data in red, gps data in black, and kalman filter in blue.

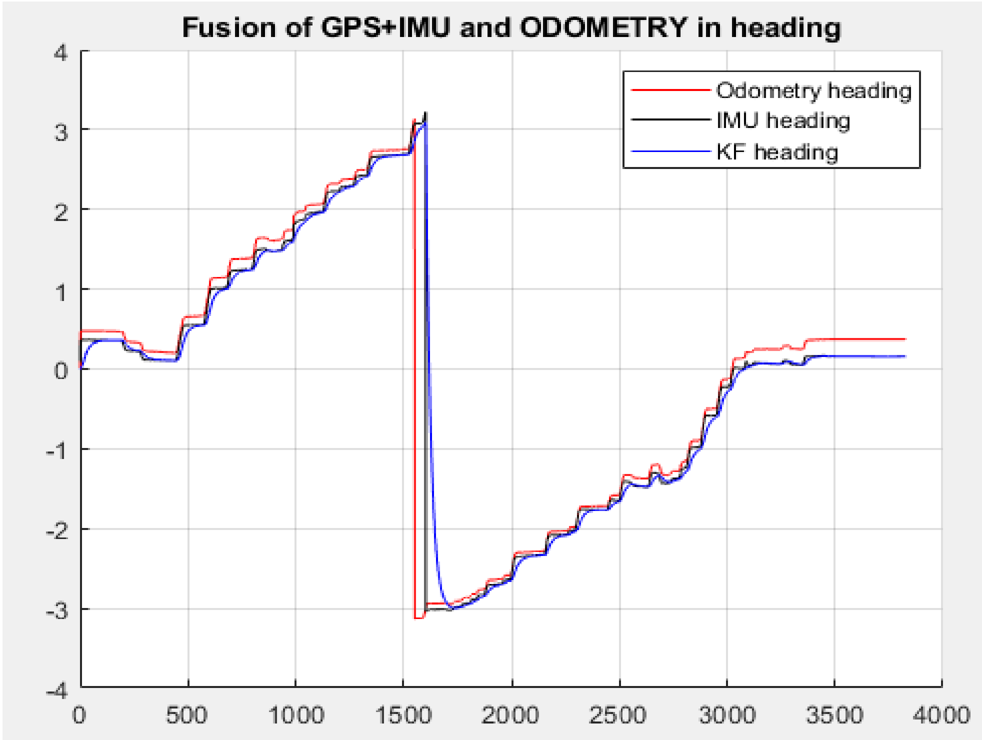

Fig. 8: Graph showing heading in radians of the robot, odometry data in red, IMU data in black, and kalman filter in blue.

Noise of IMU covariance data (ranges)

When adding noise to only certain ranges of the data (the same interval as used with the GPS covariance data). Fig 9 and Fig 10 are similar to Fig 7 and Fig 8 in that there is not much noticeable change in the position data of the robot, and a big change in the heading data. The change is less noticeable in Fig 10 due to the amount of change happening being lessened.

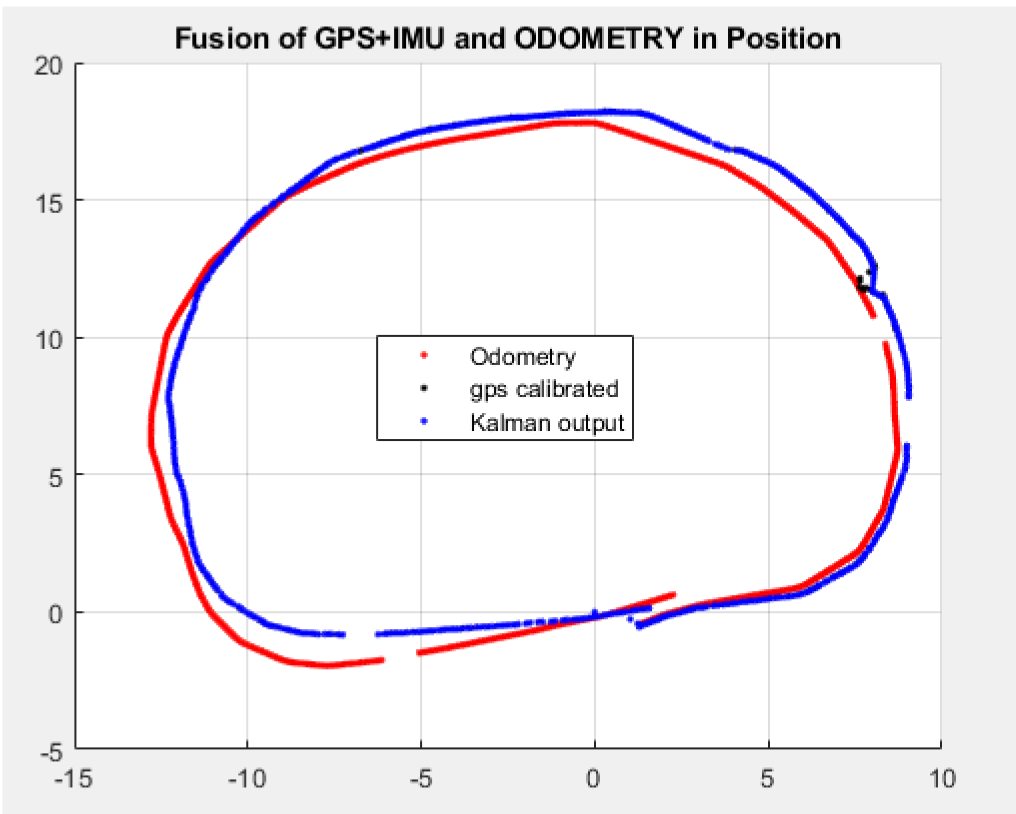

Fig. 9: Graph showing position of the robot, odometry data in red, gps data in black, and kalman filter in blue.This graph has noise in the IMU covariance matrix over intervals 1-500, 1500-2000, 2500-3000.

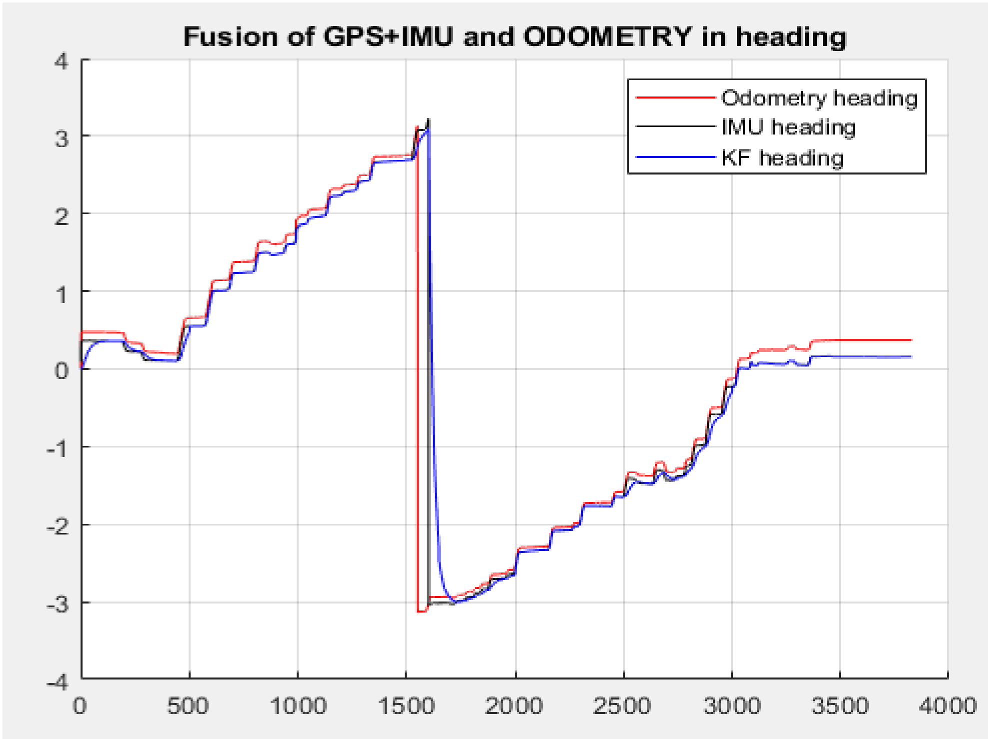

Fig. 10: Graph showing heading in radians of the robot, odometry data in red, IMU data in black, and kalman filter in blue. This graph has noise in the IMU covariance matrix over intervals 1-500, 1500-2000, 2500-3000.

E) Add noise to GPS position with changed covariance (added in (C)) to see how the Kalman Filter works. Plot and explain obtained results.
   Noise to GPS (full data set).

When adding noise to the position data of the robot, we see drastic changes as shown in Fig 11. The output of the Kalman filter is able to remove the harshness of the noise from the position data. The heading data is not changed noticeably compared to previous iterations of adding noise.

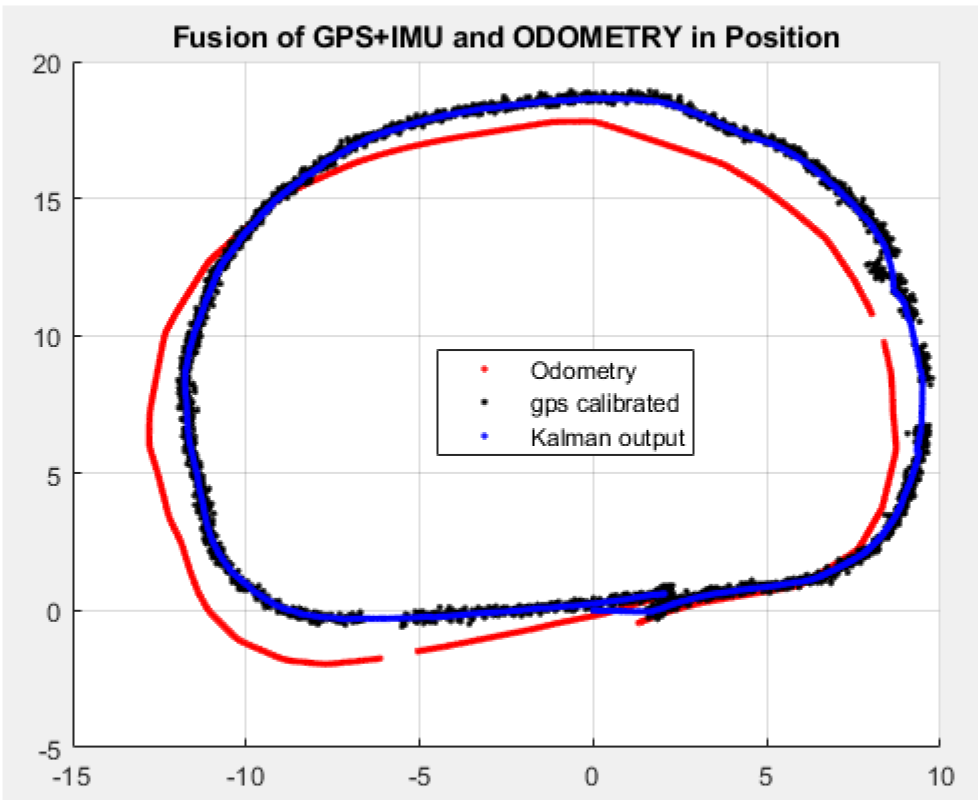

Fig. 11: Graph showing position of the robot, odometry data in red, gps data in black, and kalman filter in blue.This graph has noise in the GPS covariance matrix and GPS position.

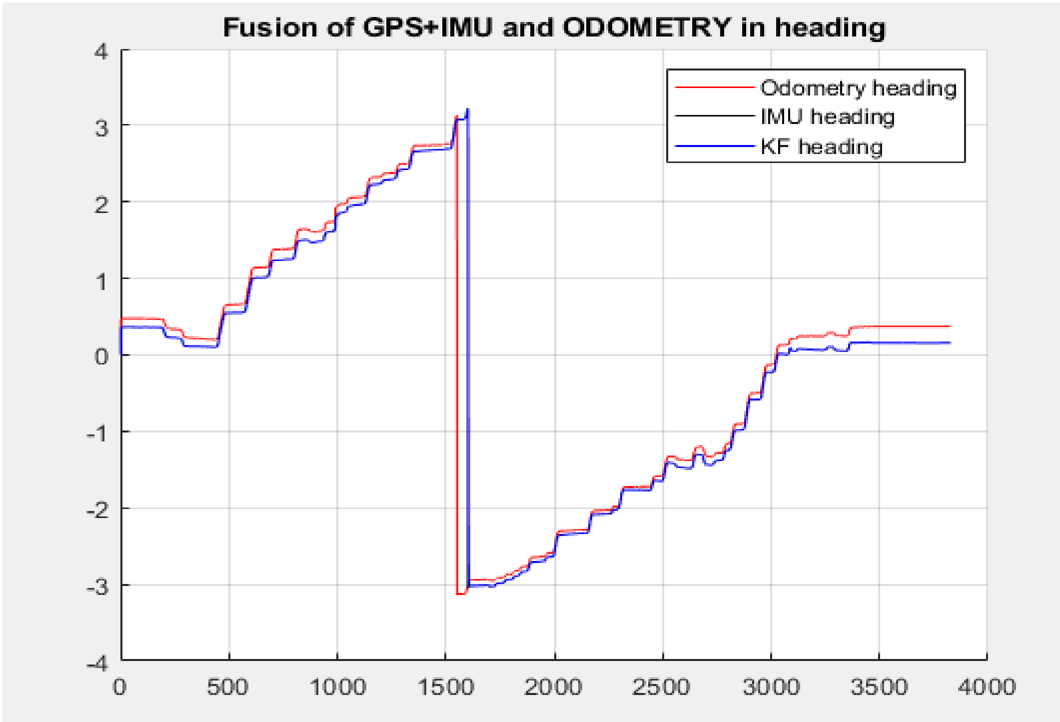

Fig. 12: Graph showing heading in radians of the robot, odometry data in red, IMU data in black, and kalman filter in blue.This graph has noise in the GPS covariance matrix and GPS position.

Noise of GPS data. (ranges)

The adding of noise to the GPS data over certain ranges (1-500, 1500-2000, and 2500-3000), is noticeably seen in Fig 13. The kalman filter is able to ignore the noise to provide an accurate estimate of the robot's position. The heading data as shown in Fig 14 does not change noticeably.

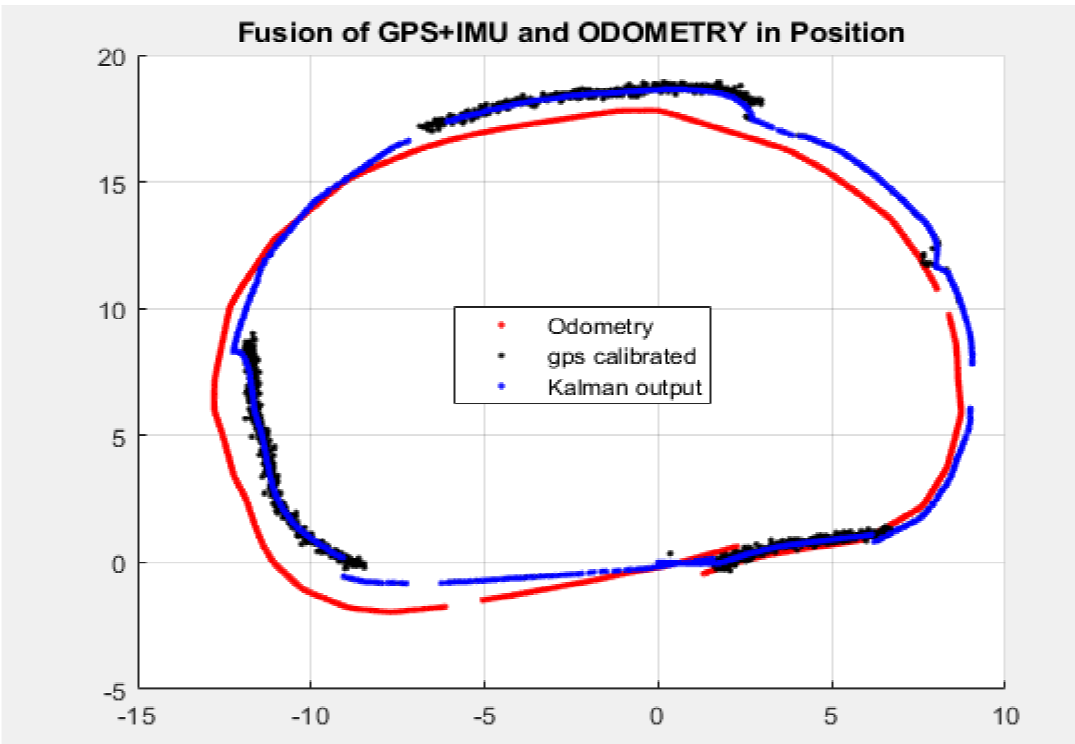

Fig. 13: Graph showing position of the robot, odometry data in red, gps data in black, and kalman filter in blue.This graph has noise in the GPS covariance matrix and GPS position over intervals 1-500, 1500-2000, 2500-3000.

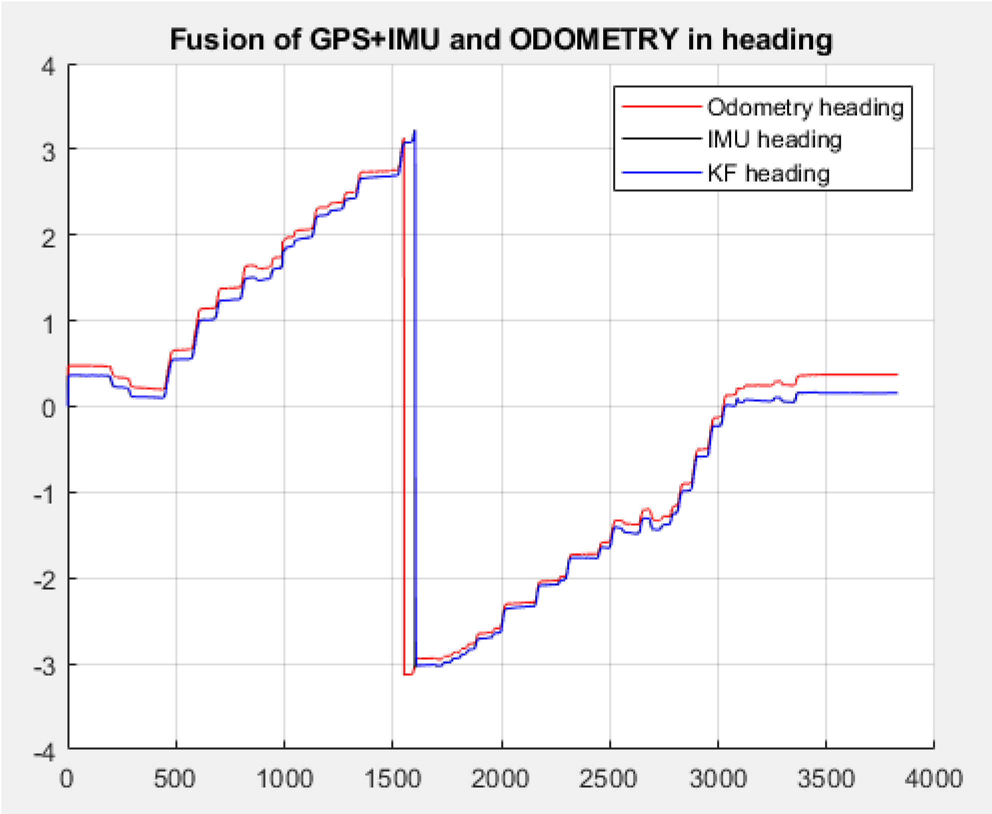

Fig. 14: Graph showing heading in radians of the robot, odometry data in red, IMU data in black, and kalman filter in blue.This graph has noise in the GPS covariance matrix and GPS position over intervals 1-500, 1500-2000, 2500-3000.

Conclusion:

All software will be provided with this report. To generate specific data for a section, parts of the code will need to be uncommented to provide the figure detailing the scenario. Most of the code was taken from slides, or provided by the professor.