EECE5554 LAB4: IMU, GPS, Magnetometer Navigation

A magnetometer measures the local magnetic field, but nearby objects create magnetic disturbances that must be mitigated for an accurate heading estimate. Distortions fall into hard iron (created by objects that produce a magnetic field) and soft iron (alterations in the magnetic field caused by metals like nickel and iron). Hard iron distortions cause permanent bias in sensor output, and soft iron distortions stretch or distort the magnetic field. Hard iron distortions have a larger contribution to the uncorrected error than soft iron. Calibration using hard and soft iron compensation can mitigate these distortions.

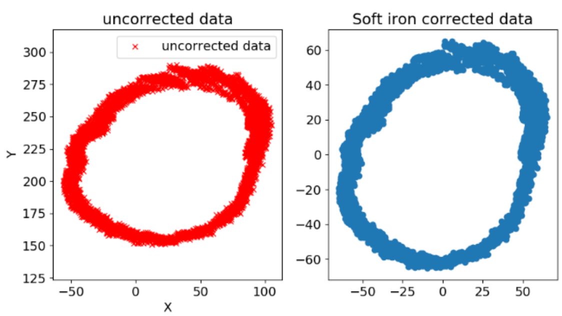


Figure: Uncorrected Mag Data vs Corrected Mag data

Calibration: It consists of two steps: hard iron correction and soft iron correction. Hard iron correction is done by finding offsets for x, y, and z data, and then subtracting them from each component. Soft iron correction is done by finding the average values of x, y, and z data to calculate scale factors, which are used to scale each component. The result is calibrated magnetic field measurements. Hard iron distortions are caused by magnetic objects and create a permanent bias in the sensor output, while soft iron distortions are caused by metals such as nickel and iron and alter the shape of the magnetic field.

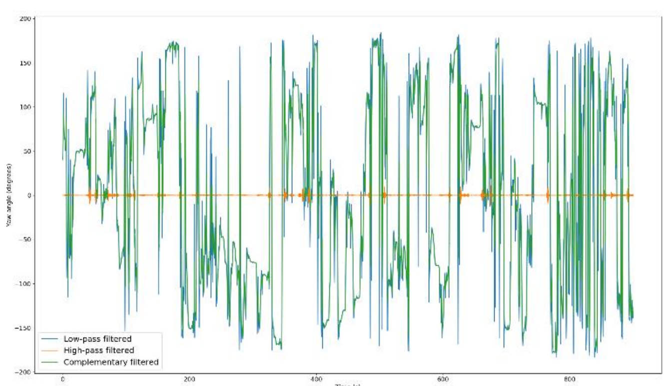


Figure: Low Pass vs High Pass vs Complimentary

Complimentary Filter: The complementary filter combines the low-pass filtered magnetometer data and high-pass filtered gyro data using a weighted sum with a parameter alpha of 0.98. Cutoff frequencies of 1 Hz and 10 Hz are used for the low-pass and high-pass filters, respectively, and the filter coefficients are determined using the Butterworth filter design method.

Yaw Data: The magnetometer-based estimates yaw data and raw yaw from magnetometer may be subject to magnetic interference, while adjusted yaw uses tilt compensation to improve accuracy. The gyro-based estimate yaw angle is not affected by magnetic interference but may experience drift over time. A combination of the magnetometer-based estimate (e.g., adjusted yaw and the gyro-based estimate (yaw angle) can provide a more robust estimate of yaw for navigation, with specific weighting depending on the application requirements.

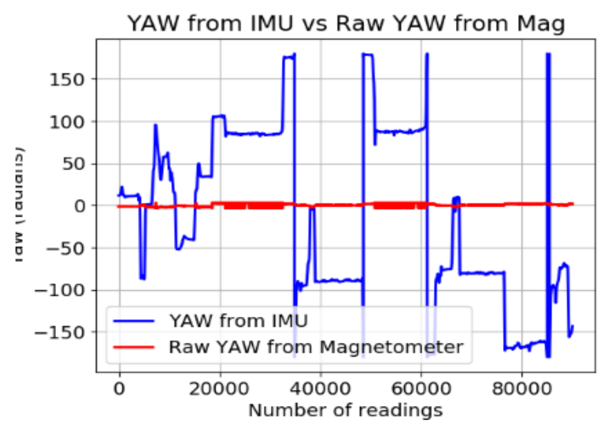


Figure: Yaw from Imu vs Raw YAW from Mag

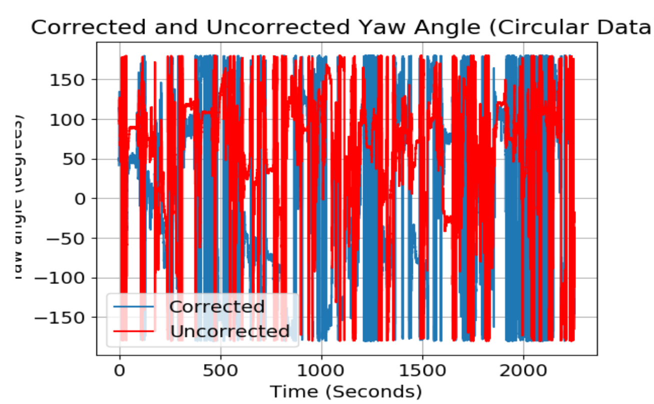


Figure: Corrected vs Uncorrected Yaw Angle

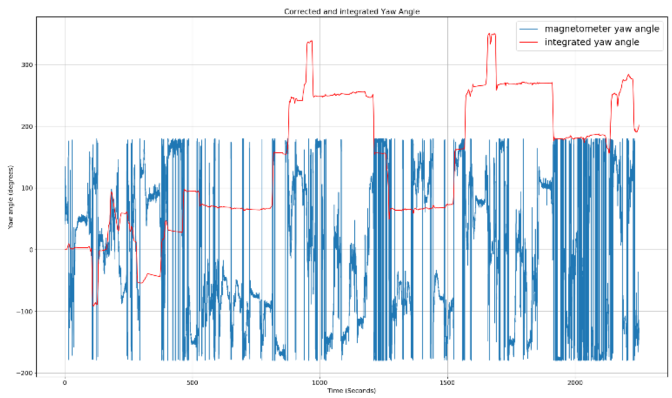


Figure: Magnetometer Yaw Angle vs Integrated Yaw

Forward Velocity Estimate: A lowpass filter is applied to the forward velocity data to remove high-frequency noise. A third-order polynomial is then fitted to the filtered velocity data to remove any long-term drift or bias. The adjusted velocity is obtained by subtracting the polynomial fit from the filtered velocity data, and any negative velocities are set to zero. This adjustment removes any long-term drift or bias in the velocity measurements that can be caused by factors such as sensor calibration errors or changes in the environment.

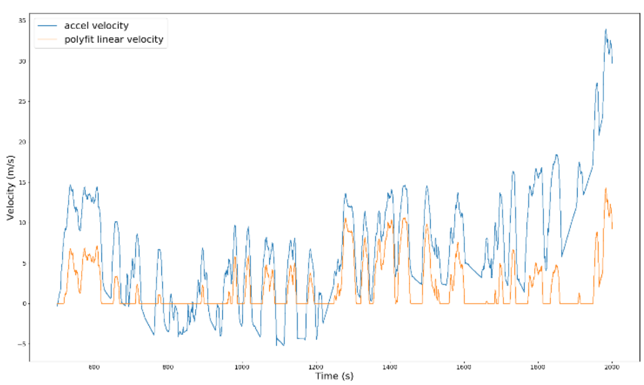


Fig: Forward Velocity before and after

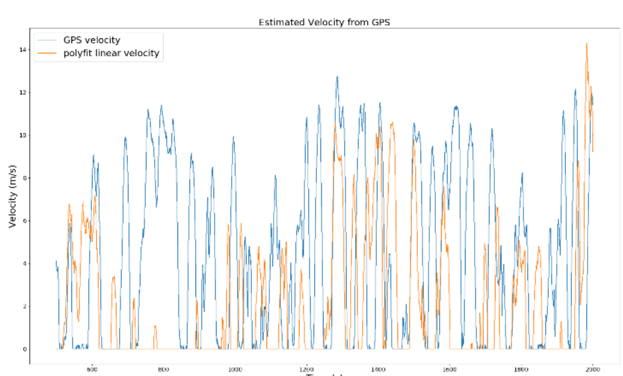
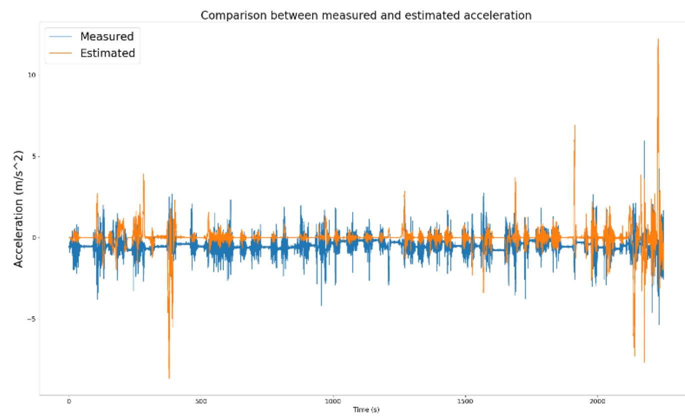


Fig: GPS velocity vs Filtered Accel Velocity

A combination of accelerometer-based and GPS-based velocity estimates can be useful in overcoming the limitations and error sources of each individual method. For example, integrating accelerometer data over short time intervals can provide high-frequency velocity estimates that are less affected by GPS noise and drift. On the other hand, GPS-based velocity estimates can be useful in correcting for any long-term bias or drift in the accelerometer-based estimates. Combining these two methods can result in a more accurate and reliable estimate of vehicle velocity.



Dead Reckoning with IMU:

Estimating Acceleration in Y direction: The tiny difference between y_est and y_obs could be due to differences in the levels of noise and bias in the sensors used to measure the angular velocity and acceleration, as well as errors in the calculations themselves, such as integration and multiplication errors. Other factors that could contribute to the discrepancy include non-linear accelerometer response, temperature changes, misalignment of the accelerometer with gravity, and amplification of errors during the integration process.

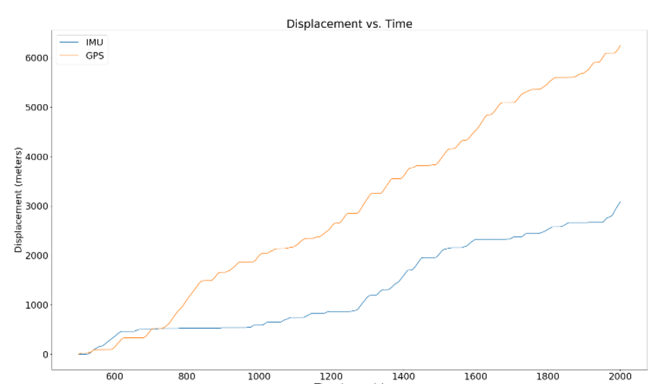


Fig: Displacement IMU vs Displacement GPS

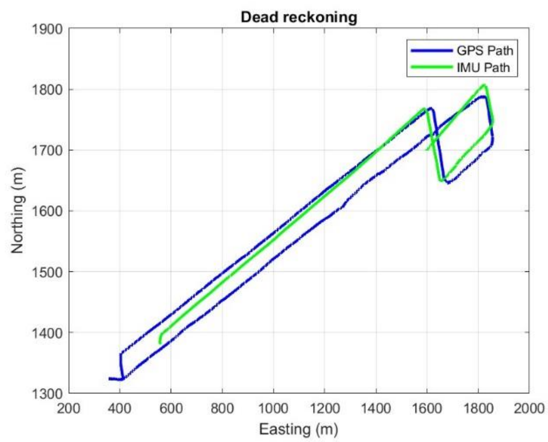


Fig: Dead Reckoning with Hard Coded Adjustments

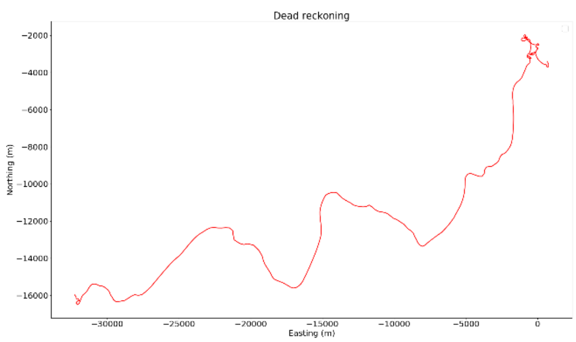


Fig: Non-Adjusted Dead Reckoning

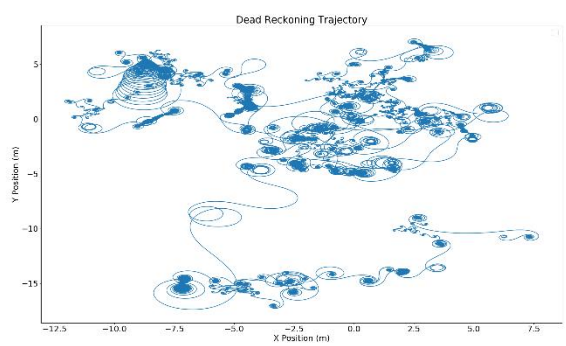


Fig: Unfiltered Dead Reckoning

Estimating Xc: Assuming that the velocity V of the center of mass of the vehicle is already estimated using dead reckoning, we can estimate xc using the formula:

$x_c = r_x = (v_x - V_x) / \omega_z$

The formula to compute v_x is $v_x = \ddot{X} + \dot{\omega} \times r_x + \omega_y v_z - \omega_z v_y - \omega_z^2 r_x$, where $\ddot{X}$ is the x-component of measured acceleration, $\dot{\omega}$ is the time derivative of angular velocity, r_x is the x-coordinate of displacement vector r, ω_y and ω_z are the y- and z-components of angular velocity, and v_y and v_z are the y- and z-components of measured velocity v.

Xc = 3.69 m

Estimate Trajectory: To simulate the trajectory of a vehicle, start by initializing position and orientation variables to zero. Then, use a loop to calculate the change in position and orientation for each time step based on the current velocity, yaw rate, and elapsed time. Update the position and orientation variables with the calculated change and store the updated position in a list for plotting the trajectory.

the dead reckoning estimates would not match the actual position measurements over time. This is because dead reckoning relies on integrating velocity and acceleration measurements over time, and any errors in these measurements can accumulate over time and result in significant drift in the estimated position. In addition, factors such as changes in vehicle dynamics, environmental conditions, and measurement noise can also contribute to errors in the dead reckoning estimates. Therefore, it is not uncommon for dead reckoning estimates to diverge from actual position measurements over time, especially in the absence of external position updates. The VectorNav VN-100 IMU has an estimated heading error of 0.15 degrees/hour and a velocity error of 0.15% (of the actual velocity). Assuming that the vehicle is traveling at a speed of 10 m/s, the velocity error would be 0.015 m/s. Using these specifications, we can estimate that the VectorNav should be able to navigate for approximately 6667 seconds or 1.85 hours without a position fix.