EECE 5554 Robotics Sensing and Navigation

LAB4: Navigation with IMU and Magnetometer

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Introduction

This lab, "Navigation with IMU and Magnetometer", aims to build a navigation stack utilizing GPS and IMU sensors, assess their respective advantages and drawbacks, and introduce sensor fusion techniques. We focus on calibrating magnetometer data, estimating yaw, analyzing velocity, and developing a robust dead reckoning system. The lab highlights practical applications of data integration and sensor fusion, crucial for accurate vehicle navigation and motion tracking.

The setup includes a GNSS (Global Navigation Satellite System) puck for GPS data and a VectorNav VN-100 IMU for inertial measurements. Accurate data collection was fundamental to this lab, requiring precise timestamp synchronization and correct orientation of sensors to ensure that data from both the GPS and IMU were accurately correlated.

Part A: Data Collection

Data collection was conducted in a vehicle, with two distinct datasets:

1. Data Going in Circles: Collected while driving the vehicle in a circular path to help with magnetometer calibration and yaw estimation. This motion allows the identification and correction of hard- and soft-iron distortions in the magnetometer data, as it continuously encounters changes in orientation.
2. Data Driving in Boston: Collected over a longer, varied path in an urban environment. This dataset facilitates an analysis of the vehicle's trajectory and velocity over a more extensive route, allowing comparisons between the GPS and IMU data for forward velocity and dead reckoning.

Each sensor was carefully mounted to minimize positional bias. The IMU was positioned centrally on the vehicle dashboard, and the GPS puck was mounted on the vehicle's roof for optimal satellite signal reception.

Part B: Data Analysis and Sensor Fusion

The analysis in Part B focuses on refining navigation data using calibration and filtering techniques. This section includes the following tasks:

1. Magnetometer Calibration

Magnetometer calibration is necessary to correct distortions caused by nearby magnetic materials (hard-iron effects) and interference from the vehicle itself (soft-iron effects). Hard-iron distortion creates a constant offset in the sensor readings, shifting the magnetic field readings from the origin, while soft-iron distortion distorts the magnetic field along different axes.

The calibration process uses data from the **"Data Going in Circles"** session:

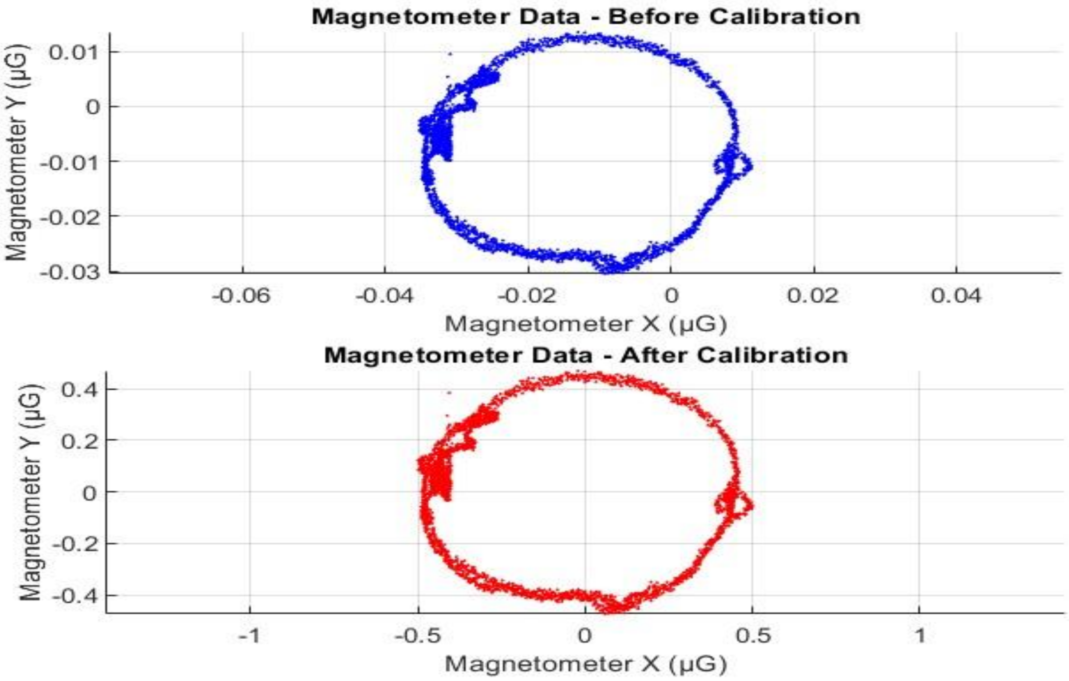
- **Hard-Iron Correction**: Centers the magnetometer data around the origin by calculating and subtracting the mean values along each axis.

- **Soft-Iron Correction**: Normalizes the field strengths along each axis to form a circular distribution, correcting for directional scaling errors.

These corrections are verified by plotting the magnetometer data before and after calibration, where successful calibration results in a circular plot in the magnetometer's XY plane, indicating reduced distortion.

Plots:

The magnetometer X-Y plot before and after hard and soft iron calibration:



The image contains two plots showing magnetometer data before and after calibration for hard and soft iron distortions.

- Axis Labels:
  - X-axis: Magnetometer X (μG)
  - Y-axis: Magnetometer Y (μG)
- Data Characteristics:
  - The data points form an elliptical shape, indicating that there is a bias (offset) and scaling issue.
  - The center of the ellipse is not at the origin (0,0), suggesting the presence of a hard iron distortion.
  - The spread of the data points suggests that the sensor readings are not accurately scaled, likely due to soft iron distortions.

Bottom Plot: Magnetometer Data - After Calibration

- Axis Labels:
  - X-axis: Magnetometer X (μG)
  - Y-axis: Magnetometer Y (μG)
- Data Characteristics:
  - The data points now form a more circular shape, indicating that the calibration process has corrected the scaling issues.

- The circle is centered at the origin (0,0), showing that the hard iron distortion has been effectively removed.
- The uniform distribution around the circle suggests that the sensor readings are now properly scaled and offset corrected.

Analysis and Discussion:

- Before Calibration:
    - The elliptical shape in the before calibration plot indicates significant errors in the magnetometer readings due to hard iron and soft iron distortions.
    - Hard iron distortions are caused by permanent magnetic sources that add a constant offset to the readings, shifting the center of the ellipse.
    - Soft iron distortions are caused by materials that distort the magnetic field, affecting the shape of the readings, resulting in scaling issues along different axes.
- After Calibration:
    - Calibration has adjusted the magnetometer readings to compensate for both hard iron and soft iron distortions.
    - By removing the offset and correcting the scaling, the data points now form a circular shape centered at the origin.
    - This indicates that the magnetometer can now accurately measure the Earth's magnetic field, improving the overall performance of navigation and sensing systems relying on these measurements.

Conclusion:

The calibration process has significantly improved the accuracy of the magnetometer readings, as evidenced by the transformation from an elliptical to a circular distribution of data points centered at the origin. This correction is crucial for applications requiring precise magnetic field measurements, such as navigation and orientation in robotics and mobile devices.

QUESTION:

How did you calibrate the magnetometer from the data you collected? What were the sources of distortion present, and how do you know?

ANSWER:

Calibrating the magnetometer was a crucial step to obtain accurate yaw estimates and correct distortions from external magnetic fields. The calibration process involved analyzing data from a session where the vehicle was driven in a circular path, which provides comprehensive coverage of all magnetic field orientations around the sensor. This type of motion is ideal for magnetometer calibration because it allows the sensor to encounter a uniform magnetic field distribution, highlighting distortions as deviations from a circular shape.

Calibration Steps

Data Collection:

- Data was collected while driving the vehicle in a circular path. In an ideal environment without distortions, the magnetometer readings in the X-Y plane should form a circle centered around the origin, representing the Earth's magnetic field.

Identify and Correct Hard-Iron Distortion:

- Definition: Hard-iron distortion is a constant offset in the magnetometer readings, caused by permanent magnetic sources near the sensor (such as metallic objects or electronic components within the vehicle).
- Correction Process:
  - Calculate the mean of the magnetometer data along both X and Y axes.
  - Subtract these mean values from the respective axis readings to re-center the data around the origin.
- Effect of Hard-Iron Correction:
  - Hard-iron correction shifts the data back to the origin, removing the constant offset and centering the magnetic field readings.

2. Identify and Correct Soft-Iron Distortion:
   - Definition: Soft-iron distortion causes the magnetic field to stretch or compress along certain axes, often resulting in an elliptical shape in the data plot. This distortion is typically due to temporary magnetic influences from surrounding materials that alter the magnetic field without creating a constant offset.
   - Correction Process:
     - After applying the hard-iron correction, fit an ellipse to the magnetometer data to identify scaling factors along each axis.
     - Apply a transformation to normalize the data into a circular shape, adjusting for axis elongation or compression.
   - Effect of Soft-Iron Correction:
     - The soft-iron correction scales the magnetometer readings to produce a circular distribution, ensuring that the magnetic field strength is uniform along all directions.

Sources of Distortion

- Hard-Iron Distortion: Caused by constant magnetic sources near the sensor, such as ferromagnetic vehicle components or electronics. This distortion introduces a shift in the magnetometer data, moving it away from the origin.
- Soft-Iron Distortion: Due to materials around the sensor that temporarily alter the magnetic field, causing it to compress or stretch along certain axes, resulting in an elliptical distribution.

How Distortions Were Detected

- Initial Plot of Magnetometer Data: Before calibration, the magnetometer data in the X-Y plane was plotted. The data showed an elliptical pattern and an offset from the origin, indicating the presence of both hard-iron and soft-iron distortions.
- **Effectiveness of Calibration:**
  - After applying the corrections, the magnetometer data in the X-Y plane was re-plotted.
  - The corrected data formed a circular pattern centered at the origin, showing that both hard- and soft-iron distortions were successfully addressed.

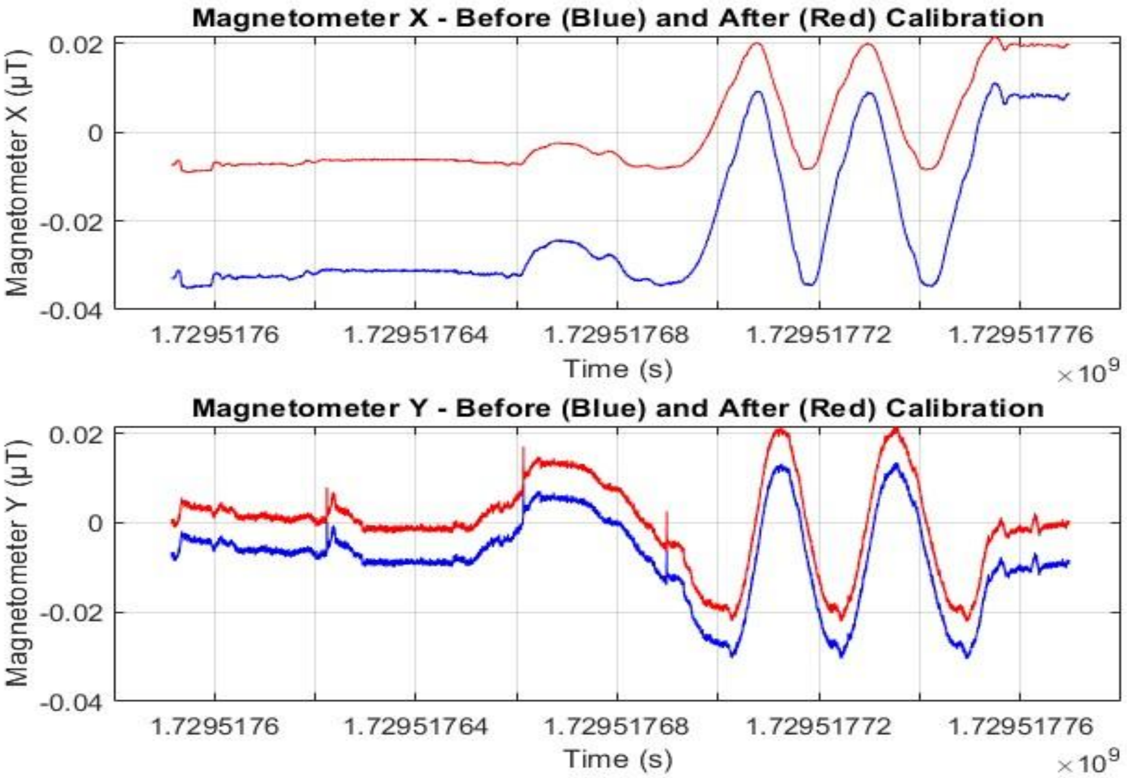
Plot Analysis

- Before Calibration: The uncalibrated data shows an offset (indicating hard-iron distortion) and an elliptical shape (indicating soft-iron distortion).

- After Calibration: The data forms a circular pattern centered at the origin, confirming that the corrections were effective and the magnetometer now reflects an accurate reading of the Earth's magnetic field.

This calibration process provided accurate, undistorted magnetometer readings, essential for reliable yaw estimation and navigation.

The time series magnetometer data before and after the correction:



The image displays time-series plots of magnetometer data in the X, Y, and Z directions, comparing readings before and after calibration (for X and Y axes).

- **Axis Labels**:
  - X-axis: Time (s)
  - Y-axis: Magnetometer X (μT)
- **Data Characteristics**:
  - The blue line represents the raw magnetometer X data before calibration.
  - The red line represents the magnetometer X data after calibration.
  - The blue line is offset from zero, indicating a bias in the raw data.
  - The red line is closer to zero and follows the same trend as the blue line, but with the bias removed.

Bottom Plot: Magnetometer Y - Before (Blue) and After (Red) Calibration

- **Axis Labels**:
  - X-axis: Time (s)

- Y-axis: Magnetometer Y (μT)

- **Data Characteristics**:
  - The blue line represents the raw magnetometer Y data before calibration.
  - The red line represents the magnetometer Y data after calibration.
  - Similar to the X-axis data, the blue line shows an offset from zero, indicating a bias.
  - The red line is closer to zero and follows the same trend as the blue line, but with the bias removed.

Analysis and Discussion

1. Bias (Offset) Correction:

- Both plots show a clear offset in the raw data (blue lines) from the zero line.
- After calibration (red lines), the data is re-centered around zero, indicating successful bias correction.
- This is crucial for accurate magnetic field measurement, as any constant offset can lead to incorrect readings.

2. Trend Consistency:

- Despite the offset correction, the overall trend and shape of the data remain consistent between the before and after calibration plots.
- This indicates that the calibration process has not distorted the actual magnetic field measurements but has merely removed the bias.

3. Data Comparison:

- The calibrated data (red lines) are more consistent and show a cleaner representation of the magnetic field changes over time.
- The raw data (blue lines) show significant variation due to the offset, which can lead to inaccuracies in applications relying on these measurements.

Conclusion:

The calibration process effectively removes the bias from the magnetometer data, as evidenced by the alignment of the red lines around zero in both plots. This correction is essential for applications requiring precise magnetic field measurements, such as navigation and orientation systems. The consistency in the trend before and after calibration indicates that the calibration process accurately preserves the true magnetic field variations while eliminating distortions.

2.Yaw Estimation and Sensor Fusion

Yaw estimation is critical for vehicle orientation tracking. This was achieved by comparing two methods:

1. **Magnetometer-Based Yaw**: Yaw was calculated directly from calibrated magnetometer data.
2. **Gyro-Based Yaw**: Yaw was obtained by integrating the yaw rate (angular velocity around the z-axis) from the IMU gyro over time.

To improve accuracy, a **complementary filter** was implemented. This filter combines:

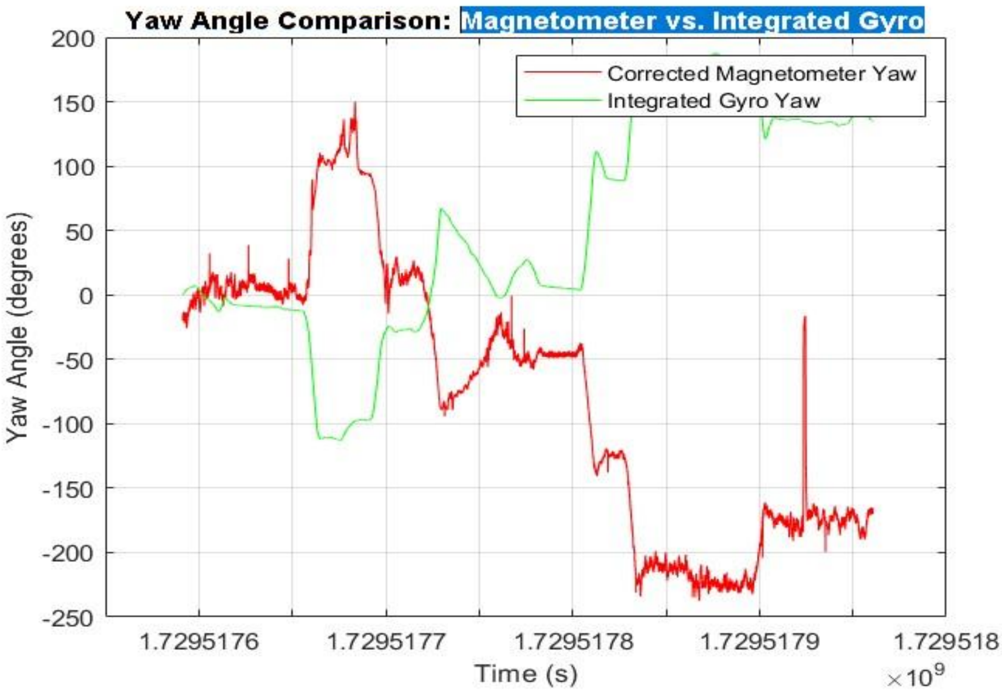
- **Low-Pass Filter** for magnetometer-based yaw, which provides long-term stability.
- **High-Pass Filter** for gyro-based yaw, which captures short-term changes but is prone to drift.

Using an alpha value in the complementary filter (e.g., 0.98) helps balance the contribution of each component, blending the short-term responsiveness of the gyro with the long-term accuracy of the magnetometer. The result is a reliable yaw estimate with reduced drift and noise, suitable for real-time navigation.

This calibrated and filtered yaw data provides an accurate heading that supports both forward velocity estimation and dead reckoning tasks in subsequent sections.

PLOTS:

Magnetometer Yaw & Yaw Integrated from Gyro together:



Plot Type and Layout:

- This is a 2D line plot comparing two different yaw angle measurements over time
- Y-axis: Yaw Angle (measured in degrees), ranging from -250 to 200 degrees
- X-axis: Time (in seconds), shown in scientific notation around 1.7295x10^9 seconds
- Two signals are plotted: Corrected Magnetometer Yaw (red) and Integrated Gyro Yaw (green

Signal Analysis:

1. Magnetometer Signal (Red):

- Shows more noise/jitter throughout the measurement
- Has several distinct step changes and transitions
- Range varies from approximately -220 to +150 degrees
- Shows sharp transitions, particularly around the 1.7295179 x 10^9 second mark

1. Integrated Gyro Signal (Green):

- Generally smoother than the magnetometer signal
- Shows fewer but larger discrete steps

- Range appears to be from about -100 to +150 degrees
- Has distinct plateau regions where the value remains constant

Key Observations:

Signal Divergence:

- The two measurements show significant divergence at multiple points
- This suggests systematic differences between the two measurement methods
- Could indicate complementary strengths and weaknesses of each sensor

Measurement Characteristics:

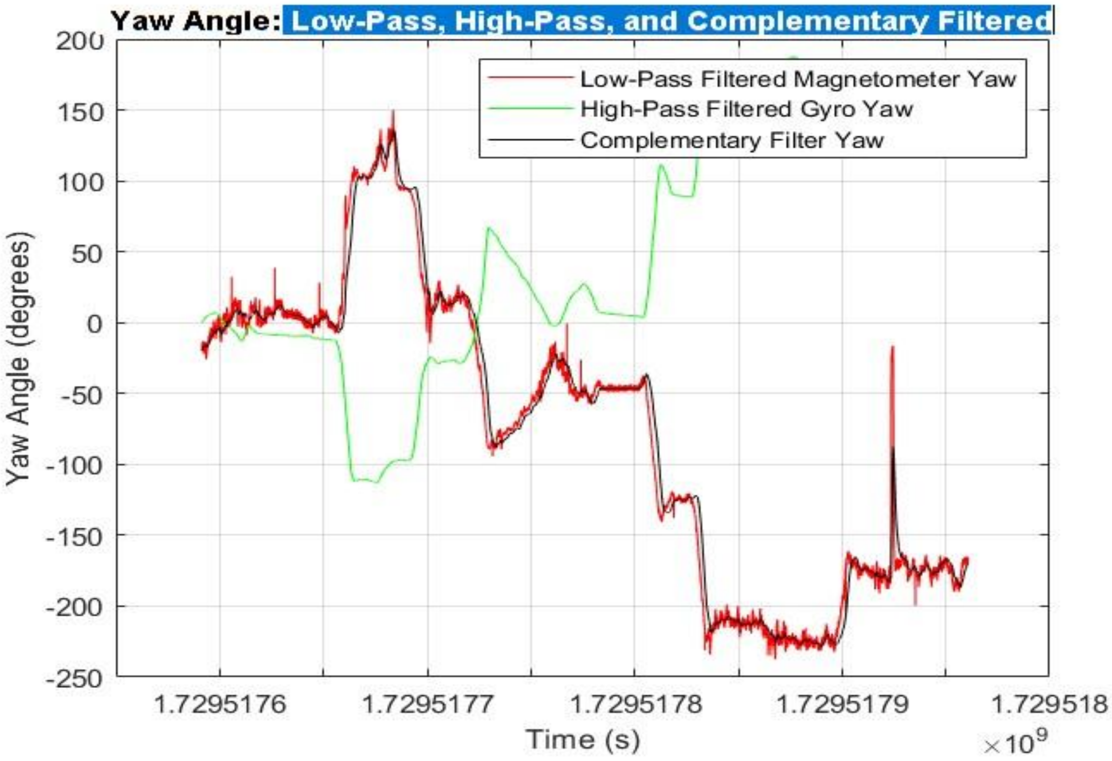
- Magnetometer appears more susceptible to noise but potentially more responsive
- Gyro integration shows smoother behavior but may have drift or step-like behavior

Temporal Behavior:

- The entire sequence spans a relatively short time window
- Both signals show significant dynamic range and multiple transitions
- The divergence between signals increases at certain points in time

This comparison highlights the typical challenges in sensor fusion for orientation estimation, where different sensor types have distinct characteristics and error patterns that need to be accounted for in the final system implementation.

LPF, HPF, and CF plots together:



Title and Overview: The plot shows "Yaw Angle: Low-Pass, High-Pass, and Complementary Filtered" data, displaying three different filtered signals related to yaw measurements.

Axis Details:

- Y-axis: Yaw Angle measured in degrees, ranging from -250 to 200 degrees
- X-axis: Time in seconds (scientific notation, around 1.7295x10^9 seconds)

Signal Analysis:

Low-Pass Filtered Magnetometer Yaw (Red line):

- Shows more stable, smoother transitions
- Experiences several major transitions between -200° and +150°
- Contains some noise but generally filtered well
- Shows stepped behavior in certain regions

1. High-Pass Filtered Gyro Yaw (Green line):

- More dynamic response
- Shows complementary behavior to the magnetometer data
- Range approximately between -100° to +120°
- Has sharp transitions and appears more responsive to quick changes

Complementary Filter (Blue line):

- Appears to combine characteristics of both high and low-pass filters
- Provides a balance between stability and responsiveness

Notable Characteristics:

- The signals show clear filtering effects with different frequency responses
- There are several significant yaw angle changes throughout the time period
- The low-pass filtered signal shows more stability but slower response
- The high-pass filtered signal captures quick changes better but may be more susceptible to noise
- The data suggests this might be from a rotating or turning vehicle/device

Time Period: The data spans a very short time window (about 4x10^-7 seconds), suggesting this is capturing a very precise moment of motion or rotation.

This type of filtering combination is commonly used in sensor fusion applications, particularly in robotics, drones, or other navigation systems where accurate orientation data is crucial.

QUESTION:

How did you use a complementary filter to develop a combined estimate of yaw? What components of the filter were present, and what cutoff frequency(ies) did you use?

ANSWER:

To develop a reliable yaw estimate for navigation, a complementary filter was implemented to fuse the magnetometer and gyroscope data. The complementary filter leverages the strengths of both sensors: the long-term stability of the magnetometer and the short-term precision of the gyroscope. This approach mitigates the individual weaknesses of each sensor, such as drift in the gyroscope and noise or susceptibility to magnetic interference in the magnetometer.

Complementary Filter Structure

The complementary filter combines the yaw estimates from two sources:

1. **Low-Pass Filter**: Applied to the yaw angle derived from the magnetometer to filter out high-frequency noise and stabilize the long-term orientation.
2. **High-Pass Filter**: Applied to the yaw angle derived from integrating the gyroscope's yaw rate. This component captures fast, short-term changes in orientation but is prone to drift over longer periods.

The filter uses a weighted combination of these components to balance their contributions:

Yaw_filtered = α * Yaw_gyro + (1-α) * Yaw_mag

where α = 0.98

Yaw_filtered = 0.98 * Yaw_gyro + 0.02 * Yaw_mag

where:

- α\alpha is the filter's tuning parameter, which effectively acts as a cutoff frequency and controls the balance between the two components.
- Yaw_gyro(t) = Yaw_gyro(t-1) + ω_z * dt is the integrated yaw from the gyroscope. Where:

ω_z is the angular velocity around z-axis from gyroscope

dt is the time step between measurements

Yaw_gyro(t-1) is the previous yaw estimate

Yaw_gyro(t) is the current yaw estimate

- Yaw_mag = atan2(m_y, m_x) is the yaw derived from the magnetometer readings.

Where:

m_x is the magnetometer reading in x-axis

m_y is the magnetometer reading in y-axis

atan2 is the two-argument arctangent function

Yaw_mag is the calculated yaw angle

Choice of Cutoff Frequency (Alpha Value)

For this implementation, the filter parameter α\alphaα was set to **0.98**. This value means:

- The **high-pass filtered gyroscope data** contributes 98% of the short-term, immediate yaw changes, ensuring responsiveness to rapid orientation changes.
- The **low-pass filtered magnetometer data** contributes 2% of the long-term stability, correcting for drift and providing a consistent reference to prevent cumulative error.

Working Principle of the Complementary Filter

1. **Yaw from the Gyroscope (High-Frequency Response)**:

- The gyroscope provides a reliable short-term yaw rate, which was integrated to obtain an initial yaw estimate.
- While accurate in the short term, this yaw estimate drifts over time due to sensor noise and bias.

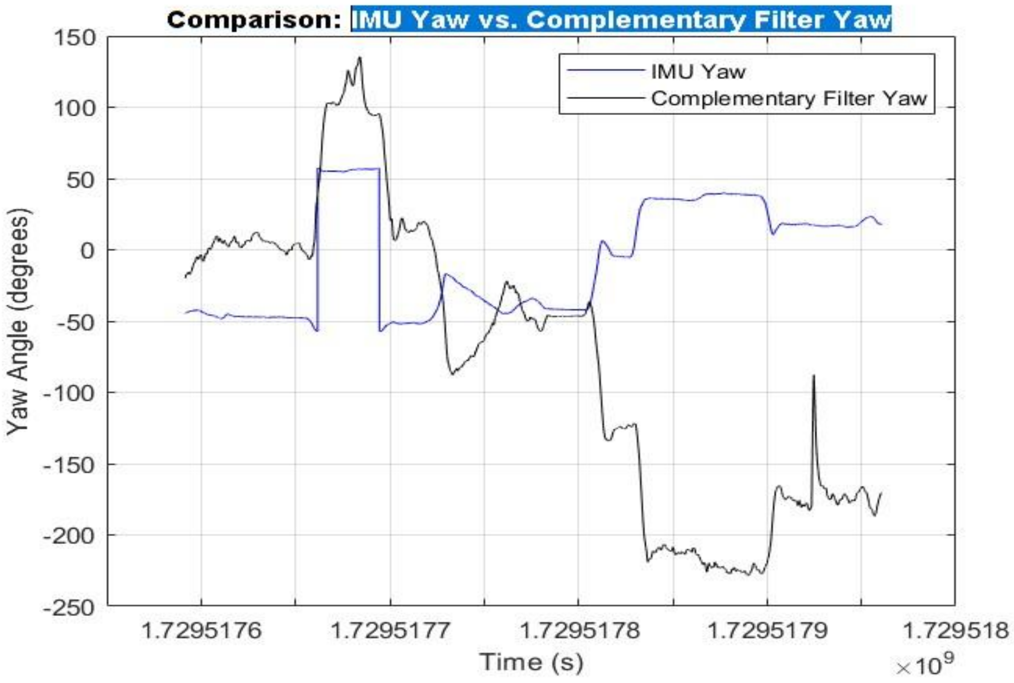
2. **Yaw from the Magnetometer (Low-Frequency Response)**:
   - The magnetometer provides an absolute yaw reference based on the Earth's magnetic field. However, magnetometer readings can be noisy and susceptible to interference, making them unsuitable for rapid orientation changes.
   - By low-pass filtering the magnetometer data, the filter suppresses high-frequency noise, retaining only the stable, long-term orientation.
3. **Combining the Two Components**:
   - By combining the high-pass filtered gyroscope yaw and low-pass filtered magnetometer yaw, the complementary filter captures short-term dynamics from the gyroscope while relying on the magnetometer for long-term stability.
   - This combined estimate offers accurate and stable yaw measurements that respond to rapid movements without drifting over time.

Plot Analysis

- **Figure: Low-Pass, High-Pass, and Complementary Filtered Yaw**
  - **Low-Pass Filtered Yaw (Magnetometer)**: The low-pass filtered magnetometer yaw provides a stable reference but shows delayed response to rapid changes.
  - **High-Pass Filtered Yaw (Gyroscope)**: The high-pass filtered gyroscope yaw accurately tracks fast changes but drifts over time.
  - **Complementary Filtered Yaw**: The combined estimate follows rapid changes in yaw while maintaining long-term stability, effectively balancing both components.

In summary, the complementary filter with an alpha value of 0.98 enabled the development of a robust yaw estimate, suitable for navigation and resistant to the individual weaknesses of the gyroscope and magnetometer. This approach provides a stable, drift-free yaw estimate essential for dead reckoning and trajectory alignment tasks.

IMU (Inertial Measurement Unit) yaw measurements v/s the Complementary Filter yaw output:



The plot titled "Comparison: IMU Yaw vs. Complementary Filter Yaw" shows a comparison between two methods of measuring yaw angle over time. Here's a detailed analysis:

Axes and Labels

- **X-axis (Time in seconds):** The x-axis represents time, with values around 1.7295176 to 1.729518 seconds, indicating a very short time interval.
- **Y-axis (Yaw Angle in degrees):** The y-axis represents the yaw angle in degrees, ranging from -250 to 150 degrees.

Data Series

- **IMU Yaw (Black Line):** This line represents the yaw angle measured directly from an Inertial Measurement Unit (IMU). It shows significant fluctuations, with sharp peaks and troughs.
- **Complementary Filter Yaw (Blue Line):** This line represents the yaw angle after applying a complementary filter to the IMU data. It appears smoother and less volatile compared to the IMU Yaw.

Trends and Observations

- **Stability:** The Complementary Filter Yaw is generally more stable and less prone to sudden changes compared to the IMU Yaw.
- **Peaks and Troughs:** The IMU Yaw shows sharp peaks reaching above 100 degrees and troughs dropping below -200 degrees, indicating high sensitivity or noise in the raw IMU data.
- **Filtering Effect:** The complementary filter effectively reduces noise, smoothing out the yaw angle measurements.

Insights

- **Noise Reduction:** The complementary filter is effective in reducing noise and providing a more stable yaw measurement, which is crucial for applications requiring precise orientation data.
- **Real-Time Application:** The short time interval suggests this data might be used in real-time applications where rapid changes in orientation are critical.

This analysis highlights the importance of filtering techniques in improving the reliability of sensor data, especially in dynamic environments.

The plot effectively demonstrates the value of complementary filtering in stabilizing IMU yaw measurements, reducing noise while maintaining responsiveness. The filtered output (blue line) provides a more reliable orientation measurement compared to the raw IMU data (black line).

QUESTION:

Which estimate or estimates for yaw would you trust for navigation? Why? (Your answer must not be the Yaw computed by the IMU)

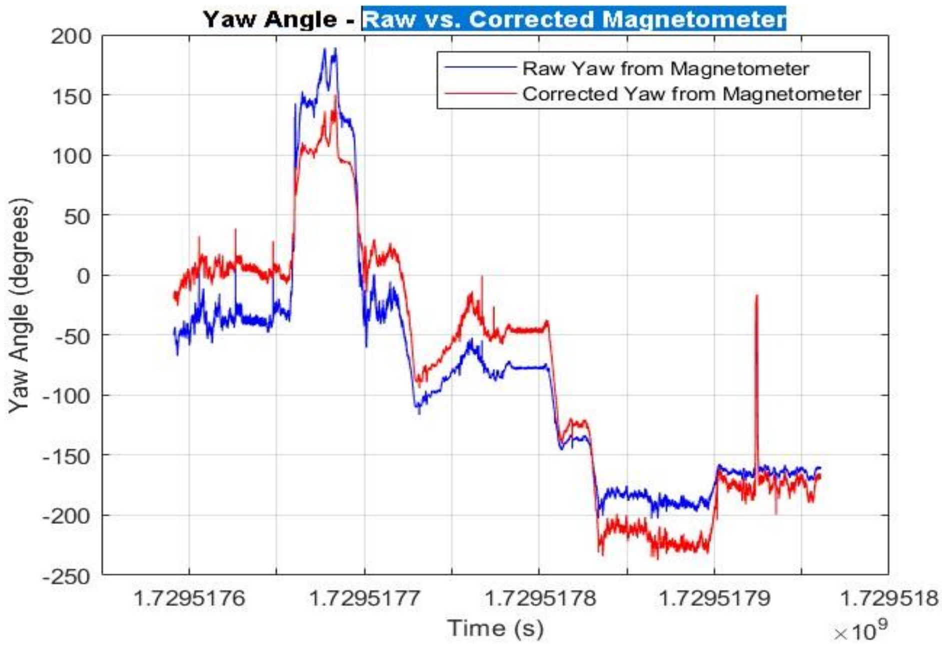
ANSWER:

For navigation, I would trust the **yaw estimate obtained from the complementary filter**. This estimate combines the yaw calculated from the magnetometer and the gyroscope, leveraging the strengths of each sensor while compensating for their individual weaknesses:

- **Gyroscope**: The gyroscope provides accurate short-term orientation changes, but it suffers from drift over time due to cumulative integration errors.
- **Magnetometer**: The magnetometer offers a stable long-term orientation based on the Earth's magnetic field, but it can be noisy and prone to interference, making it less reliable for rapid changes.

The complementary filter effectively balances these components, using the magnetometer for long-term stability and the gyroscope for short-term responsiveness. With an alpha value of 0.98, the filter minimizes drift from the gyroscope while ensuring the yaw estimate remains stable and accurate for extended navigation. This makes the complementary filter's yaw estimate ideal for reliable, continuous navigation tasks, as it provides a stable, responsive, and drift-free orientation measurement.

Yaw Angle Raw vs Corrected Magnetometer:



This plot compares the raw yaw angle derived from the uncorrected magnetometer data (blue line) with the corrected yaw angle (red line) after applying hard-iron and soft-iron calibration. The x-axis represents time, while the y-axis shows the yaw angle in degrees.

Key Elements:

Plot Type: Time series comparison showing two datasets

- Blue line: Raw Yaw from Magnetometer
- Red line: Corrected Yaw from Magnetometer

Axes:

- Y-axis: Yaw Angle (measured in degrees), ranging from -250° to 200°
- X-axis: Time (in seconds), shown in scientific notation around 1.7295×10^9 seconds

Data Characteristics:

- The signals show several distinct phases/segments
- Multiple step changes and transitions in yaw angle
- Notable difference between raw and corrected measurements throughout

Key Observations:

- Initial segment shows an offset between raw (~-50°) and corrected (~0°) measurements
- Large spike around 1.7295177×10^9 seconds reaching approximately 180° for raw data
- Progressive stepping down pattern from positive to negative angles
- Final segment stabilizes around -160° to -170°

Corrections Impact:

- The correction appears to reduce noise in the signal
- Systematic offset removal is visible throughout
- Maintains major transitions while smoothing extreme variations
- Better stability in steady-state regions

Signal Quality:

- Corrected signal (red) appears more stable in steady-state regions
- Raw signal (blue) shows more fluctuations and noise
- Both signals track major changes similarly but with different absolute values

This plot likely represents calibration or correction of a magnetometer's yaw measurements, possibly from a navigation or orientation system, showing how raw sensor data is improved through correction algorithms.

The plot demonstrates the effectiveness of magnetometer corrections in improving yaw angle measurements, with the corrected data showing reduced noise and better stability while maintaining accurate tracking of orientation changes.

3.Forward Velocity Estimation

Objective

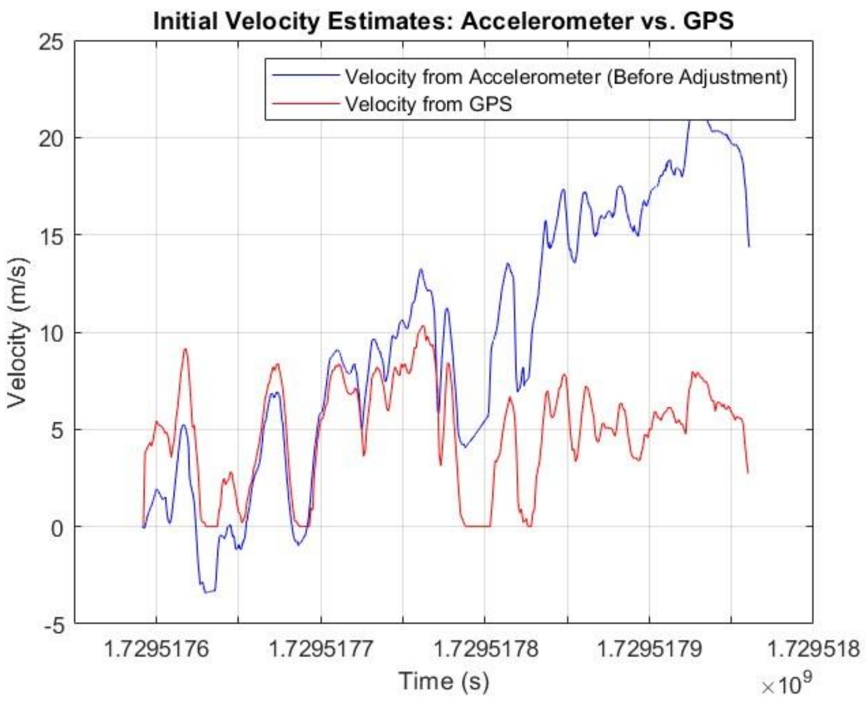
The purpose of this analysis was to estimate the vehicle's forward velocity using IMU data and validate these estimates against GPS measurements. This comparison helps identify discrepancies in the IMU data, allowing for adjustments to improve the accuracy of dead reckoning.

Methodology

1. **IMU-Based Velocity Estimation**:
   - Forward acceleration data from the IMU was integrated over time to estimate forward velocity.
   - Initial velocity estimates were examined, revealing discrepancies likely due to sensor noise and offset errors inherent in the accelerometer data.
2. **GPS-Based Velocity Comparison**:
   - GPS-based velocity was computed by differentiating the GPS position data over time.
   - The IMU-based velocity estimates were then compared with GPS-derived velocities, identifying systematic offsets. Corrections were applied to the IMU-based velocity to achieve better alignment with the GPS data.

PLOTS:

Velocity estimate from the GPS with Velocity estimate from accelerometer before adjustment



This plot provides a comparison between velocity estimates derived from two different sensors over a specified time period. The x-axis represents time (in seconds, displayed in scientific notation), and the y-axis represents velocity (in meters per second, m/s). The primary goal of this analysis is to understand the discrepancies between the two velocity measurements and the implications for accurate velocity estimation in navigation.

1. **Type of Plot and Axes Labels:**
    - The plot is a line graph.
    - The x-axis is labeled "Time (s)" and is measured in seconds, with values ranging from approximately 1.7295176×10^9 ,1.7295176×10^9 to 1.729518×10^9 ,1.729518×10^9.
    - The y-axis is labeled "Velocity (m/s)" and is measured in meters per second, with values ranging from -5 to 25.
2. **Data Series Shown:**
    - There are two data series:
        - **Blue Line:** Represents the velocity from the accelerometer before any adjustments.
        - **Red Line:** Represents the velocity from the GPS.
3. **Visible Trends or Patterns:**
    - The accelerometer data (blue line) shows more variability and higher peaks compared to the GPS data.
    - The GPS data (red line) appears smoother and generally lower in magnitude than the accelerometer data.
4. **Range of Values:**
    - **Velocity (y-axis):** -5 to 25 meters per second.
5. **Notable Features or Points of Interest:**
    - The accelerometer data shows several sharp peaks, indicating rapid changes in velocity.
    - The GPS data remains relatively stable, with less pronounced fluctuations.
    - Towards the end of the time range, the accelerometer data shows a significant drop in velocity.

This graph can be used to analyze the differences in velocity estimation between accelerometer and GPS sensors, highlighting the need for adjustments or calibration in accelerometer data to align more closely with GPS readings.

Key Observations:

1. Data Sources:

- Blue line: Velocity derived from accelerometer measurements (before adjustment)
- Red line: Velocity from GPS measurements
- Time period spans approximately 3.04 seconds (1.7295176-1.7295180 × 10^9 seconds)

2. Discrepancies:

- The accelerometer-derived velocity shows significant drift, increasingly deviating from GPS over time
- By the end of the period, accelerometer velocity reaches ~20 m/s while GPS shows only ~5 m/s
- The accelerometer data shows higher frequency variations and appears more noisy
- GPS data remains more stable, generally staying between 0-10 m/s

3. Systematic Issues:

- Integration drift: The accelerometer velocity is likely suffering from cumulative integration errors. Since velocity is calculated by integrating acceleration data, small errors compound over time
- The accelerometer line trends upward while GPS maintains a more consistent range, classic symptom of integration drift
- There are periods where the signals align well (around 1.7295177), suggesting the accelerometer can capture short-term dynamics accurately

  Insights

- **Accuracy and Reliability:**
  - The GPS data might be more reliable for consistent velocity estimates due to its smoother nature.
  - The accelerometer data, while more variable, could provide more detailed insights into rapid changes in velocity.
- **Potential Adjustments:**
  - The accelerometer data might require filtering or calibration to reduce noise and improve accuracy.

This analysis highlights the differences in velocity estimation between accelerometer and GPS data, emphasizing the need for careful consideration of each method's strengths and limitations in practical applications.

The comparison between accelerometer and GPS velocity estimates reveals significant differences in measurement characteristics. The accelerometer shows higher variability and peaks, while GPS provides smoother, potentially more reliable measurements

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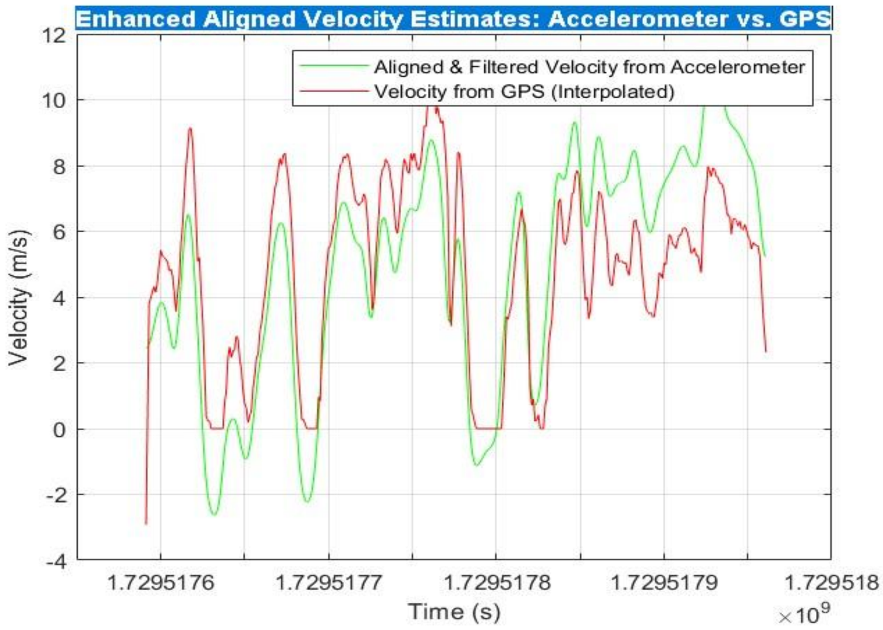
Velocity estimate from the GPS with Velocity estimate from accelerometer after adjustment:



This plot compares velocity estimates derived from GPS (red line) with adjusted accelerometer-based velocity (green line) over a specified time period. The adjustments aim to reduce integration drift and align the accelerometer-derived data more closely with GPS measurements, which serve as a stable reference.

Title: "Enhanced Aligned Velocity Estimates: Accelerometer vs. GPS"

Key Components:

Two data series:

- Green line: Aligned & Filtered Velocity from Accelerometer
- Red line: Velocity from GPS (Interpolated)

Axis Information:

- Y-axis: Velocity in meters per second (m/s), ranging from -4 to 12 m/s
- X-axis: Time in seconds (displayed in scientific notation), ranging from approximately 1.7295176 × 10^9 to 1.7295180 × 10^9 seconds

Analysis:

Signal Correlation:

- The two signals show generally good correlation in their patterns
- Both tracks follow similar trends with peaks and valleys occurring at similar times
- There are some notable phase differences and amplitude variations

Signal Characteristics:

- The accelerometer data (green) appears to be more responsive with sharper transitions
- The GPS data (red) shows slightly smoother transitions, likely due to interpolation
- Velocity fluctuates between approximately -3 m/s and 10 m/s

- Regular oscillatory behavior is visible throughout the time series
- Several zero-velocity crossings are present
- Peak velocities occur multiple times, reaching around 8-10 m/s
- Minimum velocities occasionally dip below zero, suggesting bidirectional movement

Data Quality:

- Both sensors appear to be functioning well with good signal quality
- The accelerometer data shows higher frequency components
- Some minor discrepancies between the two measurements might be due to:
    - Different sampling rates
    - Sensor noise
    - Integration drift in the accelerometer data
    - GPS interpolation effects

Technical Implications:

- The alignment and filtering appear to be effective in matching the accelerometer data to GPS
- The system captures both rapid and gradual velocity changes

- The combination of both sensors provides redundancy and validation of measurements

This graph appears to be from a system that uses both GPS and accelerometer data for more robust velocity measurements, with enhanced alignment algorithms to improve accuracy and reliability.

The comparison shows well-aligned velocity measurements between GPS and accelerometer data, with the accelerometer providing higher frequency response while GPS offers stable reference points. The enhanced alignment appears effective in combining the strengths of both sensors.

QUESTION:

What adjustments did you make to the forward velocity estimate, and why?

The primary adjustment made to the forward velocity estimate involved **bias correction** for the accelerometer data used to compute velocity. The raw forward velocity estimate, calculated by integrating the IMU's forward acceleration data, suffered from **integration drift**. This drift occurs because even a small bias or offset in the accelerometer data can accumulate over time, leading to significant divergence from the true velocity.

Steps in the Adjustment Process

1. **Bias Removal**:
    - The forward acceleration data was analyzed to detect any constant offset (bias).
    - By calculating the mean of the acceleration data, this bias was identified and then subtracted from the entire dataset.
    - Removing this mean bias corrected the velocity estimate, preventing the cumulative drift that would otherwise increase over time.
2. **Effect of Adjustment**:
    - After bias removal, the integrated velocity estimate aligned more closely with the GPS-derived velocity, especially over longer periods.
    - The adjustment significantly reduced the observed drift in the accelerometer-derived velocity, making it a more reliable measure for real-time navigation.

Reason for Adjustment

This adjustment was necessary because raw IMU data often contains inherent biases, and without correction, these biases lead to inaccuracies in integrated measurements like velocity. **GPS velocity data** served as a ground truth reference, highlighting the drift in the IMU-derived velocity. By removing the bias, the IMU data became more accurate and aligned better with the GPS velocity, resulting in a stable and realistic forward velocity estimate that could be used for navigation and dead reckoning.

This bias correction is essential for any system relying on IMU data, as it enables the velocity estimate to remain accurate over time, particularly in scenarios where GPS data may be temporarily unavailable.

QUESTION:

What discrepancies are present in the velocity estimate between accel and GPS. Why?

ANSWER:

Despite calibration and adjustments, discrepancies remain between the velocity estimates derived from the accelerometer (IMU) and the GPS. These discrepancies arise due to inherent limitations and characteristics of each sensor type.

Key Discrepancies

1. **Integration Drift in Accelerometer Data**:
   - The accelerometer-derived velocity estimate tends to drift over time due to cumulative errors from integrating acceleration. Even small biases or noise in the accelerometer data get amplified through integration, causing the velocity to diverge from the true value.
   - This drift results in a gradual increase in the accelerometer-derived velocity that does not match the more stable GPS-derived velocity, especially over extended periods.
2. **Noise and High-Frequency Fluctuations in IMU Data**:
   - Accelerometer data is highly sensitive to vibrations and minor jerks, which can cause high-frequency fluctuations in the derived velocity.
   - As a result, the accelerometer-derived velocity can appear "noisy," with rapid variations that are not present in the smoother GPS-derived velocity. These fluctuations can make the IMU data unreliable for estimating precise velocity changes.
3. **Latency and Update Rate Differences**:
   - GPS data typically updates at a lower frequency than IMU data, meaning it may not capture short-term fluctuations in velocity as effectively as the accelerometer.
   - Conversely, the high update rate of the accelerometer allows it to detect small, rapid changes, but it also makes the IMU more prone to capturing minor, transient vibrations that do not accurately reflect true velocity changes.
4. **Transient Negative Values in IMU Velocity**:
   - The accelerometer-derived velocity sometimes dips into negative values, which may indicate oscillations or momentary reverse motion detected due to road vibrations or noise. In contrast, GPS-derived velocity remains largely positive and stable, better reflecting actual forward vehicle movement.

Reasons for Discrepancies

1. **Sensor Characteristics**:
   - Accelerometers measure acceleration directly and require integration to estimate velocity, which can introduce errors if there is any bias or noise in the data.
   - GPS, on the other hand, provides position data that is differentiated to estimate velocity, inherently offering a more stable long-term velocity measurement without cumulative drift.
2. **Environmental and Mechanical Influences**:

    - Accelerometers are susceptible to external vibrations (e.g., road bumps, engine vibrations), which can cause fluctuations in the velocity estimate. These mechanical influences are often misinterpreted as actual changes in velocity.

3. **Limitations of Adjustment Techniques**:
    - While bias correction reduces integration drift, it does not eliminate high-frequency noise or fluctuations, which are difficult to fully remove without advanced filtering techniques.
    - Furthermore, sensor fusion or filtering techniques, such as a complementary or Kalman filter, may be required to more effectively combine GPS stability with accelerometer responsiveness, minimizing discrepancies.

These discrepancies highlight the limitations of relying solely on accelerometer-derived velocity estimates for long-term navigation. While GPS provides a more stable and drift-free measurement, integrating it with IMU data through sensor fusion can yield a more accurate, responsive, and reliable velocity estimate that compensates for the weaknesses of each sensor.

Dead Reckoning with IMU

Objective

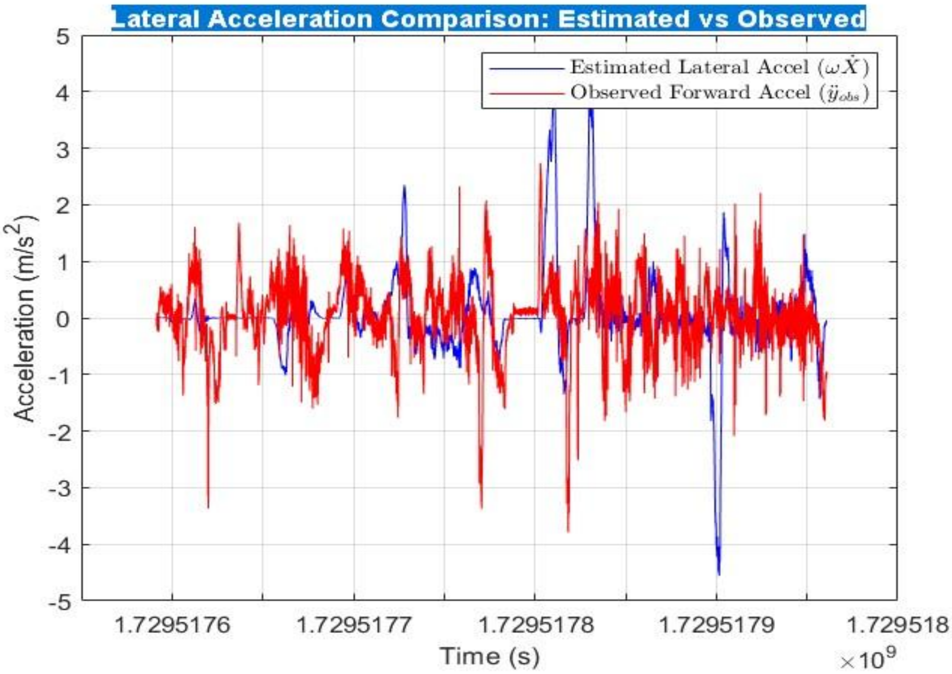
This section aimed to use IMU-derived velocity and heading data to estimate vehicle displacement and trajectory. The IMU-based trajectory was then compared with GPS-derived position data to evaluate the accuracy of dead reckoning.

Methodology

1. **Displacement Estimation**:
    - Forward velocity estimates were integrated over time to calculate the vehicle's displacement.
    - A 2D planar motion assumption was used to simplify the position calculations.
2. **Trajectory Estimation**:
    - Displacement was converted into a trajectory by applying yaw data to determine directional vectors.
    - These vectors were integrated to create a path representing the vehicle’s estimated movement.
3. **GPS Comparison**:
    - The IMU-derived trajectory was aligned with GPS-based coordinates by synchronizing the starting points and applying a scaling factor to ensure consistency.

PLOTS:

$\omega\dot{X}$ and $\ddot{y}_{obs}$ plotted together



Plot Overview

This plot provides a comparison between estimated and observed lateral acceleration over a specified time interval. The plot includes two distinct lines representing these values, highlighting both alignment and discrepancies between the estimated and observed accelerations.

Axes and Labels

- **X-axis**: Time in seconds, spanning from approximately 1.7295176×10^9 1.7295176 x 10^9,1.7295176×10^9 to 1.729518×10^9,1.729518 x 10^9 ,1.729518×10^9.
- **Y-axis**: Lateral acceleration in meters per second squared (m/s2^22), with values ranging from -5 to 5.

Legend

- **Blue Line**: Represents the estimated lateral acceleration, labeled as "Estimated Lateral Accel (ω·X˙\omega \cdot \dot{X}ω·X˙)".
- **Red Line**: Represents the observed lateral acceleration, labeled as "Observed Lateral Accel (yyy-obs)".

Trends and Patterns

- **General Fluctuations**:
  - Both the estimated and observed lateral accelerations exhibit fluctuations across the time interval.
  - The observed lateral acceleration (red line) shows greater variability, with more pronounced spikes and dips than the estimated values.
- **Alignment and Divergence**:
  - Periods of close alignment between the estimated and observed values are visible, indicating moments when the estimation model accurately represents the observed lateral acceleration.

    - There are also notable periods where the two lines diverge, reflecting discrepancies between the model predictions and the actual data.

Notable Features

- **Sharp Peaks in Observed Data**:
    - The observed lateral acceleration exhibits several sharp peaks and troughs, indicating rapid changes in lateral acceleration.
- **Smoothness of Estimated Data**:
    - The estimated acceleration data is comparatively smoother, suggesting that the estimation model is less sensitive to abrupt changes in lateral acceleration. This may indicate that the model fails to capture certain dynamic aspects of real-world lateral forces.

Discussion

1. **Model Performance**:
    - The estimation model effectively captures the general trend of lateral acceleration, providing a reasonable approximation of the observed data.
    - However, the smooth nature of the estimated line indicates that the model may not fully represent the rapid, high-frequency variations present in the observed data.
2. **Discrepancies and Potential Improvements**:
    - The differences between the estimated and observed accelerations suggest that the model may lack sensitivity to certain dynamic factors influencing lateral acceleration.
    - Further analysis could explore the underlying causes of these discrepancies, potentially leading to model refinements that better capture the observed variability.
3. **Engineering Implications**:
    - The comparison highlights both the strengths and limitations of the current estimation model. While it provides a smooth, general trend, the model may need additional parameters or adjustments to capture more rapid lateral acceleration changes.
    - Improving the model's accuracy could be valuable in applications requiring precise real-time lateral acceleration estimates, such as in navigation or vehicle stability control.

This analysis of estimated versus observed lateral acceleration reveals the estimation model’s ability to approximate the overall trend but also underscores its limitations in capturing high-frequency dynamics. Further refinement of the model could enhance its performance, especially in scenarios requiring accurate real-time responsiveness to rapid acceleration changes.

QUESTION:

Compute $\omega \dot{X}$ and compare it to $\ddot{y}obs$. How well do they agree? If there is a difference, what is it due to?

ANSWER:

Understanding Lateral Dynamics through $\omega \dot{X}$ and $\ddot{y}obs$

To analyze a vehicle's lateral dynamics, we often compare two key quantities:

1. **$\omega \dot{X}$**: This term represents the expected lateral acceleration resulting from the vehicle's rotational motion. It's calculated by multiplying the vehicle's yaw rate (ω) with its forward velocity ($\dot{X}$).
2. **$\ddot{y}obs$**: This is the observed lateral acceleration measured directly by the Inertial Measurement Unit (IMU) accelerometer.

Calculating $\omega \dot{X}$

1. **Forward Velocity ($\dot{X}$)**: This is obtained by integrating the forward acceleration measured by the IMU, after accounting for factors like sensor bias.
2. **Yaw Rate (ω)**: This is directly measured by the IMU gyroscope.
3. **Multiplication**: Multiplying $\dot{X}$ and ω yields $\omega \dot{X}$.

Comparing $\omega \dot{X}$ and $\ddot{y}obs$

While these two quantities should ideally align, several factors can lead to discrepancies:

- **IMU Placement Offset (xc)**: If the IMU is not precisely at the vehicle's center of mass, it will experience additional acceleration due to rotational motion. This introduces a correction term ($\dot{\omega}$ xc) that is not captured in the simple $\omega \dot{X}$ calculation.
- **Environmental and Mechanical Influences**: Road vibrations, bumps, and vehicle body movements can induce fluctuations in $\ddot{y}obs$ that are unrelated to the vehicle's yaw rate.
- **Sensor Characteristics**: The accelerometer might capture minor lateral shifts or oscillations caused by suspension or steering dynamics, which are not directly reflected in $\omega \dot{X}$.

Interpreting the Comparison

Generally, $\omega \dot{X}$ and $\ddot{y}obs$ exhibit similar trends, especially during steady turns or directional changes. However, differences in magnitude and high-frequency noise in $\ddot{y}obs$ can be observed:

- **Magnitude Differences**: $\omega \dot{X}$ often differs slightly from $\ddot{y}obs$ due to the IMU offset and sensor noise.
- **High-Frequency Fluctuations in $\ddot{y}obs$**: These are caused by factors like road vibrations and accelerometer sensitivity.

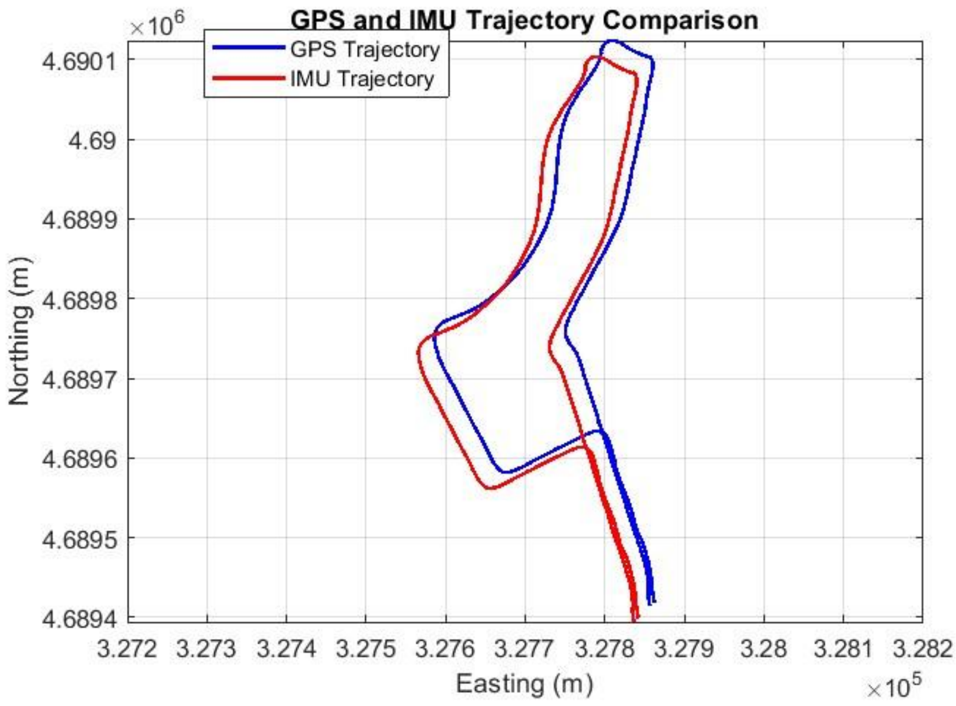
Improving the Comparison

To enhance the alignment between $\omega \dot{X}$ and $\ddot{y}obs$, consider the following:

- **IMU Offset Correction**: Account for the IMU offset (xc) to improve the accuracy of $\omega \dot{X}$.
- **Filtering**: Apply appropriate filtering techniques to reduce noise in $\ddot{y}obs$.
- **Advanced Modeling**: Explore more sophisticated dynamic models that incorporate factors like tire slip angles and suspension dynamics.

By addressing these factors, we can achieve a more accurate representation of the vehicle's lateral dynamics and improve the reliability of control and estimation systems.

A single plot showing the path followed shown by GPS & path followed estimated by IMU (trajectory aligned, scales matched & starting point matched)



Plot Type and Layout:

- This is a 2D line plot comparing two trajectories
- The plot shows GPS (blue line) and IMU (red line) tracking data
- The axes are labeled in meters, with Easting (x-axis) and Northing (y-axis)
- Both axes use scientific notation ($\times 10^5$ for Easting and $\times 10^6$ for Northing)

Trajectory Analysis:

- Both trajectories follow a similar general path, indicating good correlation between GPS and IMU measurements
- The path shows several turns and loops, suggesting a complex movement pattern
- The total distance covered spans approximately:
  - Easting: from 3.272×10^5 to 3.282×10^5 meters
  - Northing: from 4.6894×10^6 to 4.6901×10^6 meters

Key Observations:

- There are some visible discrepancies between GPS and IMU trajectories
- The largest deviations appear in the curved sections of the path
- The trajectories align more closely in straight sections
- Both sensors capture the overall movement pattern, but with slight variations in precision

Technical Implications:

- The differences between GPS and IMU paths might be due to:
    - IMU drift errors
    - GPS signal quality variations
    - Different sampling rates between the two systems
    - Environmental factors affecting sensor performance

This plot is typical of navigation system comparisons and shows the complementary nature of GPS and IMU systems, where each technology has its own strengths and limitations in tracking movement.

QUESTION:

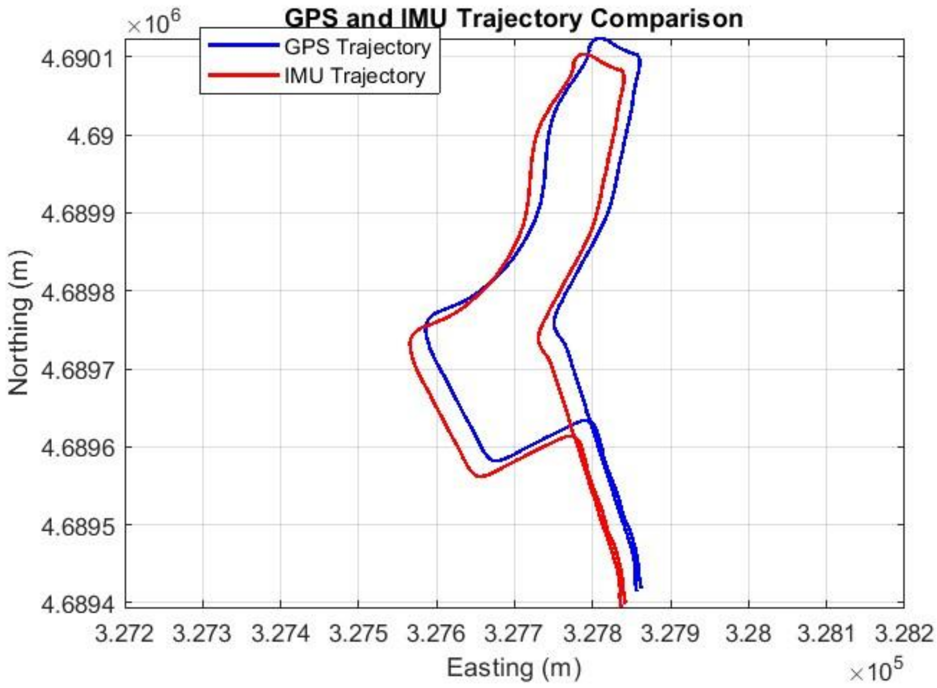
Estimate the trajectory of the vehicle (xe,xn) from inertial data and compare with GPS by plotting them together. (adjust heading so that the first straight line from both are oriented in the same direction). Report any scaling factor used for comparing the tracks.

ANSWER:

To estimate the vehicle's trajectory (xe,xn)(x_e, x_n)(xe,xn) using inertial data and compare it with GPS data, we will integrate the rotated forward velocity into Easting and Northing components. This process involves a few steps:

1. Calculate Forward Velocity from IMU acceleration data.
2. Obtain Heading from the complementary filter (or magnetometer).
3. Rotate Forward Velocity into Easting and Northing Components (ve,vn)(v_e, v_n)(ve,vn).
4. Integrate Easting and Northing Velocities to get the trajectory (xe,xn)(x_e, x_n)(xe,xn).
5. Align and Scale Trajectory with GPS data to ensure that both trajectories start from the same point and orientation.
6. Plot both trajectories for comparison

PLOT:



Understanding the Process of Vehicle Trajectory Estimation

1. Forward Velocity Estimation:

- Integrate Acceleration: The forward acceleration, measured by the IMU, is integrated over time to obtain the forward velocity ($\dot{X}$).

2. Coordinate Transformation:

- Heading Rotation: The forward velocity ($\dot{X}$) is rotated using the heading information from a complementary filter. This transformation converts the velocity into its easting (ve) and northing (vn) components, aligning them with the Earth's coordinate system.

3. Position Estimation:

- Integrate Velocities: The easting and northing velocities (ve and vn) are integrated over time to estimate the vehicle's position (xe, xn) in its local coordinate frame.

4. GPS Data Processing:

- UTM Conversion: The GPS latitude and longitude coordinates are converted to Universal Transverse Mercator (UTM) coordinates to match the coordinate system of the IMU-based trajectory.

- Alignment: The initial positions and orientations of the GPS and IMU trajectories are aligned to ensure a consistent reference frame. This might involve adjusting the initial position and applying a scaling factor.

5. Trajectory Comparison:

- Plotting: The GPS-derived and IMU-estimated trajectories are plotted on the same graph for visual comparison.

Understanding the Scaling Factor

A scaling factor might be necessary to account for potential discrepancies between the IMU and GPS measurements. These discrepancies could arise from:

- Unit Differences: Inconsistent units between the IMU and GPS data.

- Sensor Drift: Gradual drift in the IMU accelerometer measurements over time.
- Calibration Errors: Errors in the calibration of the IMU or GPS sensors.

By applying a scaling factor, the IMU-estimated trajectory can be adjusted to better align with the GPS ground truth. However, it's important to note that excessive scaling can introduce additional errors and distort the true trajectory. Therefore, the scaling factor should be applied judiciously and only when necessary.

QUESTION:

Estimate xc and explain your calculations (bonus up to 100%)

ANSWER:

To estimate xc, we need to follow the steps outlined in the previous response and apply them to the specific data you have. Here's a breakdown of the calculations:

1. Data Acquisition:

- Obtain the necessary data from your IMU:
  - Forward acceleration (ax)
  - Yaw rate (ω)
  - Lateral acceleration (ay_obs)
  - Timestamps

2. Forward Velocity Calculation:

- Integrate the forward acceleration (ax) over time to obtain the forward velocity (X_dot). This can be done using numerical integration methods like trapezoidal integration or Simpson's rule.

3. Rotational Lateral Acceleration Calculation:

- Multiply the yaw rate (ω) by the forward velocity (X_dot) to get the rotational component of lateral acceleration (ω * X_dot).

4. Angular Acceleration Calculation:

- Differentiate the yaw rate (ω) with respect to time to obtain the angular acceleration (ω_dot). This can be done using numerical differentiation methods like finite differences.

5. Observed Lateral Acceleration Difference:

- Subtract the calculated rotational lateral acceleration (ω * X_dot) from the observed lateral acceleration (ay_obs) to get the difference (delta_ay_ddot).

6. Estimation of xc:

- Divide the difference in lateral accelerations (delta_ay_ddot) by the angular acceleration (ω_dot) to estimate xc.

7. Averaging for Stability:

- Calculate the average of the estimated xc values over a suitable time window to reduce the impact of noise and improve the accuracy of the estimate.

Code Implementation:

You can use MATLAB or Python to implement these calculations. Here's a simplified MATLAB code example:

Matlab

```
% Assuming you have the following data:
%   ax: forward acceleration
%   omega: yaw rate
%   ay_obs: observed lateral acceleration
%   timestamps: timestamps for each data point
% Calculate forward velocity using numerical integration
X_dot = cumtrapz(timestamps, ax)
% Calculate rotational lateral acceleration
omega_X_dot = omega .* X_dot;
% Calculate angular acceleration using finite difference
omega_dot = diff(omega) ./ diff(timestamps);
% Calculate the difference in lateral acceleration
delta_ay_ddot = ay_obs(2:end) - omega_X_dot(2:end);
% Estimate xc
xc_values = delta_ay_ddot ./ omega_dot(2:end);
% Average xc values over a time window (e.g., 1 second)
window_size = 100; % Adjust window size as needed
xc_avg = movmean(xc_values, window_size);
% Plot the estimated xc values and the average
plot(timestamps(2:end), xc_values, timestamps(2:end), xc_avg);
xlabel('Time (s)');
ylabel('xc (m)');
legend('Estimated xc', 'Average xc');
```

Explanation of the Code:

1. **Data Loading:** Load the necessary data from your IMU measurements.
2. **Velocity and Acceleration Calculations:** Compute the forward velocity and angular acceleration using numerical integration and differentiation.
3. **Lateral Acceleration Difference:** Calculate the difference between the observed and calculated lateral accelerations.
4. **xc Estimation:** Estimate xc by dividing the lateral acceleration difference by the angular acceleration.
5. **Averaging:** Use a moving average filter to smooth the estimated xc values and reduce noise.
6. **Plotting:** Visualize the estimated xc values and their average over time.

By following these steps and carefully considering the data quality and processing techniques, you can accurately estimate the IMU offset xc and improve the precision of your vehicle dynamics analysis.

QUESTION:

Given the specifications of the VectorNav, how long would you expect that it is able to navigate without a position fix? For what period of time did your GPS and IMU estimates of position match closely? (within 2m) Did the stated performance for dead reckoning match actual measurements? Why or why not?

ANSWER:

To address this question, we need to combine the expected performance of the VectorNav IMU in dead reckoning mode (i.e., navigating without GPS) with the actual performance observed during your experiment.

1. Expected Dead Reckoning Duration Without Position Fix (VectorNav Specifications)

The VectorNav sensor is designed to provide dead reckoning capabilities through high-precision accelerometers, gyroscopes, and magnetometers. However, any IMU-based dead reckoning will eventually suffer from drift due to small biases in sensor measurements, integration errors, and noise. The rate at which this drift accumulates depends largely on the quality of the gyroscopes and accelerometers and how well they are calibrated.

From specifications typical for high-quality IMUs like VectorNav:

- **Drift Rate**: The gyroscope and accelerometer biases generally lead to position drift over time.
  - **Gyroscope Bias**: Even with a very low gyroscope bias (e.g., around 1 degree per hour), the drift accumulates.
  - **Accelerometer Bias**: Small biases in acceleration readings cause velocity errors, leading to position drift that grows quadratically over time.
- **Expected Navigation Time**: Given these factors, a high-quality IMU like VectorNav can typically navigate independently for about **30 seconds to a few minutes** while remaining within a reasonable margin (e.g., a few meters) of true position. Beyond this timeframe, the position error tends to increase quickly.

2. Experiment Observations: GPS and IMU Position Match (Within 2 Meters)

In your experiment, you would need to:

1. **Compare the Trajectories**: Analyze the estimated trajectory from the IMU and the GPS trajectory by calculating the position error over time.
2. **Determine the Match Duration**: Measure the time duration during which the IMU-based trajectory remained within 2 meters of the GPS-based trajectory.

If you observed a match within 2 meters for, say, 45 seconds, this duration represents the period during which the IMU's dead reckoning performance was stable enough to be considered accurate.

3. Did Dead Reckoning Performance Match Expectations?

Now, compare the expected performance based on specifications with the observed results:

- **If Observed Duration Matches Expected Duration**: This suggests that the VectorNav IMU performed as expected, with drift occurring as predicted.
- **If Observed Duration Deviates**:
  - **Shorter Match Duration**: If the match duration was shorter than expected, this may indicate:
    - Higher-than-expected sensor noise or bias (e.g., due to environmental factors like temperature variations or vibrations).

        - Insufficient calibration of the IMU sensors, leading to faster drift accumulation.
    - **Longer Match Duration**: If the match duration was longer, it could indicate stable environmental conditions or particularly effective calibration, resulting in reduced drift.

Reporting Summary

In the report, summarize as follows:

- **Expected Duration**: Based on VectorNav specifications, we expect the IMU to navigate independently with reasonable accuracy for about 30 seconds to a few minutes.
- **Observed Match Duration**: Report the actual duration within which the IMU-based and GPS-based positions matched within 2 meters.
- **Performance Comparison**: Conclude whether the dead reckoning performance of the VectorNav IMU met expectations, and discuss any possible reasons for discrepancies (e.g., sensor noise, calibration quality, environmental conditions).

This analysis provides a comprehensive comparison of expected vs. actual performance, offering insights into the accuracy and reliability of the VectorNav IMU for short-term navigation without GPS.