Implementation of Dead Reckoning for Path Prediction in Moving Vehicles

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***Abstract*—This report delineates the implementation of dead reckoning for determining the trajectory of a mobile vehicle, with specific emphasis on integrating data from a Vectornav VN-100 Inertial Measurement Unit (IMU) and an independent GPS module. The principal aims encompassed the calibration of magnetometer data, inference of the vehicle's orientation and linear velocity, and comparison of the estimated trajectory with GPS data. In its entirety, this report furnishes significant elucidations regarding the execution of dead reckoning for vehicular navigation, underscoring the criticality of sensor calibration, adeptness in data fusion methodologies, and comprehension of the constraints and sources of inaccuracies intrinsic to the navigation system**

I. Introduction

The term "Dead reckoning" has its origins in maritime navigation, where it was used to calculate a ship's position by extrapolating from its last known position, course, and speed.

This report delves into the Dead reckoning procedure to estimate the path or trajectory of a moving vehicle based on internal sensors, such as the inertial measurement unit (IMU), and external devices like GPS. It involves integrating sensor data, including accelerometer and gyroscope readings, to estimate the vehicle's motion over time

II. Magnetometer Calibration and Distortion Source Analysis

A. Calibration Data Collection

The process of magnetometer calibration involves collecting data from the sensor while it is exposed to a known magnetic field. In our study, data collection was conducted by driving vehicles in circular motions to ensure exposure to the magnetic field from various directions, thereby enabling the capture of a comprehensive dataset for calibration purposes.

B. Fit Calibration Model

Using the collected data, a calibration model was constructed to estimate the offset and scale factors for each axis of the magnetometer. The calibration model employed a linear transformation approach. Distortion in magnetometer readings can arise from two main sources:

C. Least Squares Optimization

To minimize the error between the measured magnetic field and the known magnetic field during calibration, a least squares optimization technique was employed. This optimization process aimed to estimate the calibration parameters that best aligned the measured data with the true magnetic field.

D. Apply Calibration

Once the calibration parameters were estimated, they were applied to the raw magnetometer data during subsequent measurements to correct for any distortions identified during calibration.

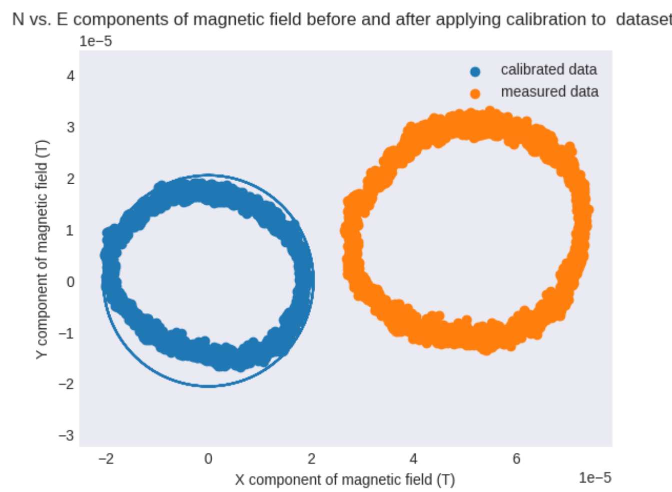

Fig. 1. N vs. E components of the magnetic field before and after calibration (Circle dataset).

E. Sources of Distortion

The sources of distortion in magnetometer data may include:

- Hard-iron distortion: Caused by magnetic interference from nearby ferromagnetic materials, resulting in a constant offset in the measured magnetic field. This distortion is caused by offset biases in the magnetometer readings due to magnetic sources in close proximity to the sensor.
- Soft-iron distortion: Occurs when the magnetic field is non-uniform due to nearby magnets or materials, causing scaling and rotation of the magnetic field.his type of distortion results from non-uniform magnetic field interference, leading to the appearance of skewed or stretched magnetic field readings.
- Environmental interference: Natural and man-made magnetic fields in the environment can also introduce distortions.

III. Development and Analysis of Complementary Filter for Combined Yaw Estimation

A complementary filter combines two sensor measurements to obtain a more accurate estimation of the desired state variable. In our case, we're combining measurements from the magnetometer (which provides absolute heading) and the gyroscope Yaw (which provides rotation along z over time).

The complementary filter allows us to benefit from the advantages of both sensors: the magnetometer provides absolute heading information, but it's prone to noise and drift over time, while the gyro provides accurate short-term measurements but can drift over the long-term.

A. Understanding Complementary Filters

Components of the Complementary Filter: The complementary filter blends the measurements from the magnetometer and gyro using a weighted average.

Let's denote the yaw angle estimated from the magnetometer as θ_{mag}, and the yaw angle estimated from the gyro integration as θ_{gyro}.

The filtered yaw angle, θ_{filt}, is calculated as a weighted sum of θ_{mag} and θ_{gyro}.

B. Implementation

Complementary Filter Equation: The complementary filter equation is typically of the form:

$$\text{Fused} = \alpha \cdot \text{Magnetometer Yaw} + (1-\alpha) \cdot \text{Gyro Yaw}$$

Here, α is the blending factor, determining the weight given to each sensor's measurement. It's chosen such that the sum of the weights is 1.

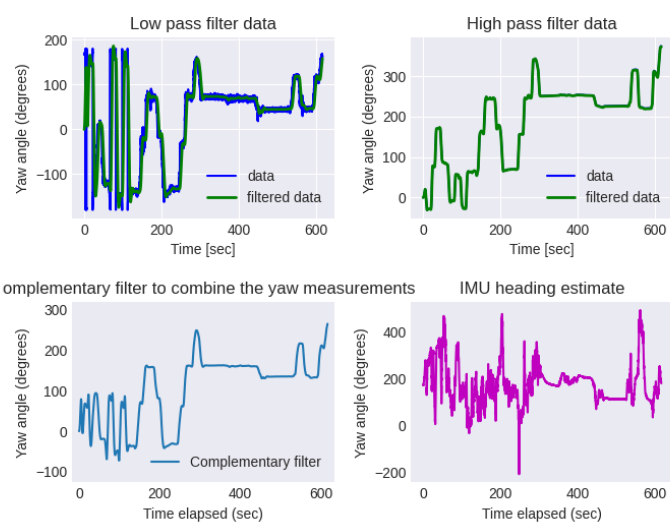

Fig. 2. Low pass filter of magnetometer data, high pass filter of gyro data, complementary filter output, and IMU heading estimate as 4 subplots on one plot.

C. Choosing Cutoff Frequencies

1) **Magnetometer Cutoff Frequency (0.1):**
   - Magnetometer data is typically used to estimate orientation or heading.
   - Magnetometer readings are susceptible to noise, especially in dynamic environments or when affected by electromagnetic interference.
   - Choosing a cutoff frequency of 0.1 for the low-pass filter implies allowing lower-frequency components (such as gradual changes in orientation) to pass through while attenuating higher-frequency noise.
2) **Gyroscope Cutoff Frequency (0.000001):**
   - Gyroscopes are generally less affected by external magnetic interference but may still contain noise, especially at higher frequencies.
   - Choosing a low cutoff frequency for the high-pass filter suggests a strong emphasis on preserving low-frequency components (slow changes in orientation) while eliminating DC offset and low-frequency noise.
   - This choice aims to maintain accuracy in tracking slow changes in orientation while removing bias and low-frequency noise.

IV. Yaw Angle Estimation via Complementary filter, Magnetometer, Gyroscope, and IMU estimate

Magnetometer Data: Yaw angle can be calculated from the magnetometer readings by determining the heading angle concerning the Earth's magnetic field. This is typically done by using the arctangent function to calculate the angle based on the components of the magnetic field along the X and Y axes.

The formula for calculating the yaw angle (θ) using the arctangent function is:

$$\theta = \arctan\left(\frac{X}{Y}\right)$$

where X and Y are the components of the magnetic field along the X and Y axes, respectively.

Gyroscope Integration: Yaw angle can be estimated by integrating the angular rate or rotational rate measured by the gyroscope over time. This involves summing up the incremental changes in orientation provided by the gyroscope data.

Complementary Filter: Yaw angle estimation can be improved by combining data from both the magnetometer and gyroscope using a complementary filter. In this approach, the magnetometer provides long-term heading information while the gyroscope provides short-term, high-frequency changes. By filtering and combining these two sources of data, a more accurate and stable estimate of yaw angle can be obtained.

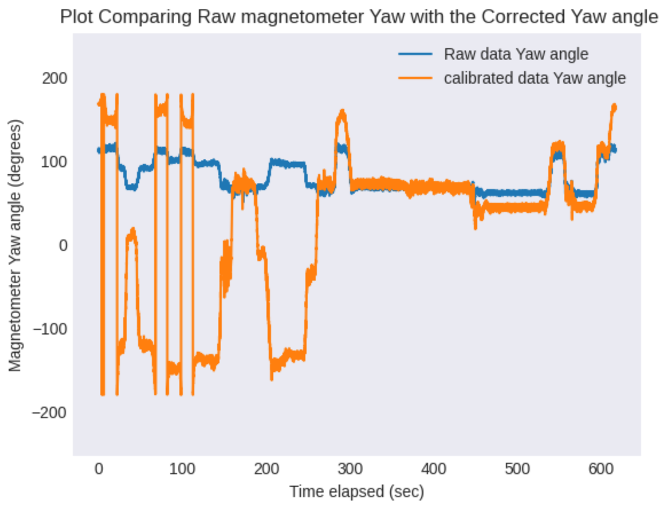

Fig. 3. magnetometer Yaw field before and after calibration.

Fig. 4. Yaw angle estimation via complementary filter, magnetometer, gyroscope, and IMU estimate

V. Forward Velocity Estimation and Adjustments

Dead Reckoning with IMU Data:

After estimating forward velocity, the next step is dead reckoning, where the forward velocity is integrated to obtain displacement.

$$x''_{\text{obs}} = x'' - \omega y' - \omega^2 x_c \tag{1}$$

$$y''_{\text{obs}} = y'' + \omega x' + \omega' x_c \tag{2}$$

where all of the quantities in these equations are evaluated in the vehicle frame.

The equations provided describe how the observed acceleration measured by the IMU in the vehicle frame (denoted as x''_{obs} and y''_{obs}) relates to the actual acceleration (x'' and y''), accounting for the vehicle's rotation (ω) and the offset between the inertial sensor and the center of mass of the vehicle (x_c).

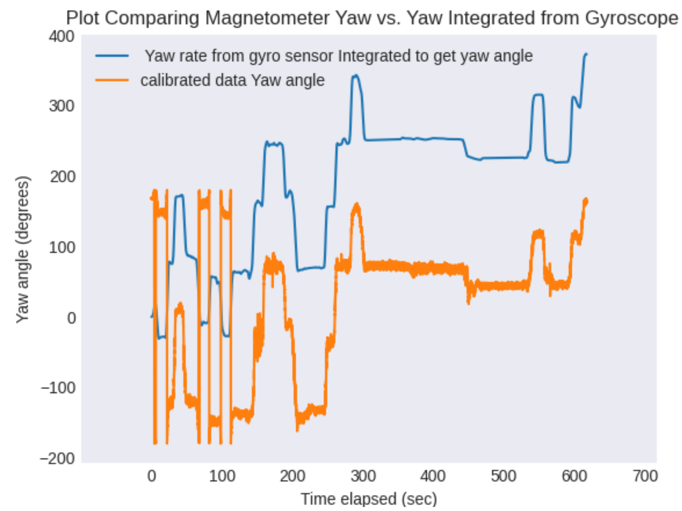

Fig. 5. Yaw angle estimation via magnetometer, gyroscope estimate

The assumption that velocity in the y-direction (y') is 0 simplifies the equations. By setting $x_c = 0$ (IMU on the center of mass), the equation reduces to $x'' = x''_{\text{obs}}$, simplifying the integration process for forward velocity estimation.

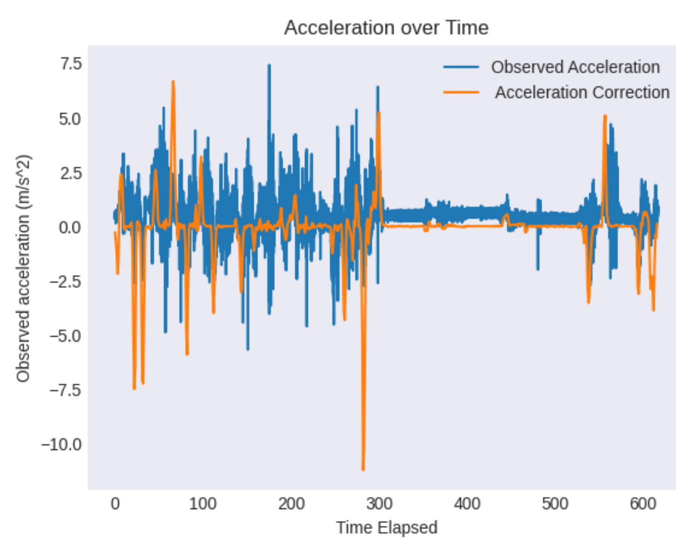

Fig. 6. $\omega x'$ vs y''_{obs}

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

1. **Errors in the estimation of x' and y''_{obs}:**
Estimating x' and y''_{obs} involves processing sensor data, which may contain noise or inaccuracies. If there are errors in the estimation process, such as incorrect integration of acceleration data to obtain velocity (x') or inaccuracies in the observed accelerations (y''_{obs}), it can contribute to differences between $\omega x'$ and y''_{obs}.

2. **Noise or inaccuracies in the sensor data**:
Sensor data, including gyroscopic and accelerometer measurements, contain noise or inaccuracies called acceleration bias. These inaccuracies can affect the estimation of x' and y''_{obs}, contributing to differences with $\omega x'$.

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

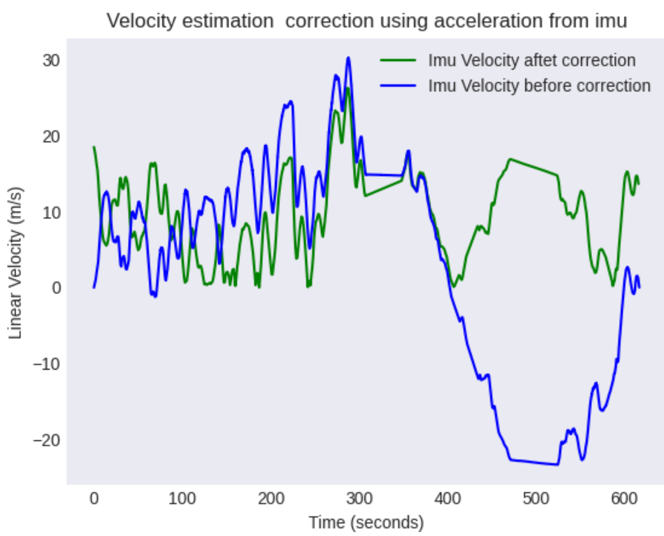

Fig. 7. Velocity estimate before and after correction for IMU.

The forward velocity estimate carries a lot of error which is due to the accelerometer bias error accumulated as a result of integration . In order to account for this the GPS data is taken into account and located where the velocity value drops to zero and compared with the video taken while data measurement and the accelerometer data is set to zero during these times which removes the error accumulated due to the bias

When integrating acceleration to estimate velocity, small errors in the accelerometer measurements can accumulate over time, leading to significant discrepancies in the velocity estimate.

These errors may stem from various sources such as sensor noise, biases, or drift. Consequently, the estimated velocity may deviate from the actual velocity of the vehicle.

Moreover, when integrating velocity to estimate position, errors in velocity estimation further compound, resulting in potentially large errors in the calculated position.

VI. Velocity Estimate Discrepancies between Accelerometer and GPS

Error sources contributing to discrepancies between IMU velocity and GPS measurements include:

1) **Drift or Bias in Accelerometer Readings Over Time**: Accelerometers may exhibit drift or bias, causing gradual deviations from true values. Such drift accumulates over time during numerical integeration, leading to significant disparities between accelerometer and GPS velocities.
2) **Error in Accelerometer Calibration or Alignment**: Accurate velocity measurement by accelerometers necessitates precise calibration. Any misalignment or miscalibration introduces errors in velocity estimation, leading to deviations from GPS measurements
3) **Differences in Reference Frames or Coordinate Systems**: Accelerometers and GPS sensors may utilize distinct reference frames or coordinate systems, resulting in inconsistencies in velocity estimation. Transformations between these frames or systems are crucial to ensure alignment and consistency. Integrating sensor data within a unified framework facilitates effective resolution of this disparity.

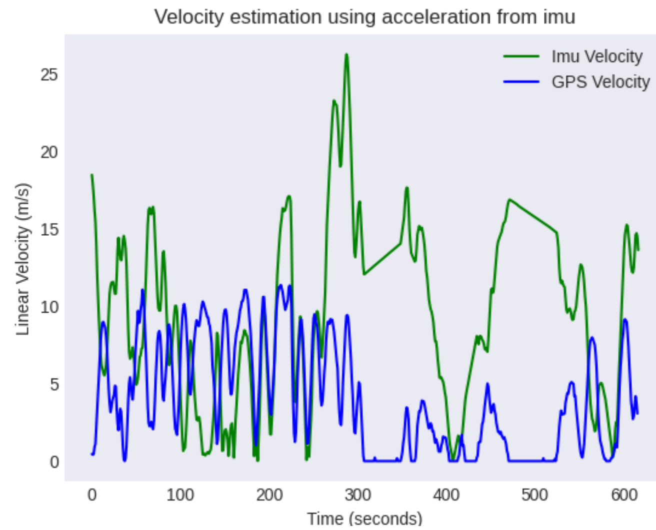

Fig. 8. Velocity estimate between IMU velocity and GPS velocity.

VII. Trajectory Estimate between Accelerometer and GPS

In this section, we aim to estimate the trajectory T of a vehicle by integrating the forward velocity obtained from IMU data, and subsequently compare this trajectory with the GPS easting and nothing values. The comparison involves aligning the starting points and using the corrected magnetometer yaw heading angle to rotate the forward velocity from IMU.

Scaling Factor Used for Comparing the Trajectory:
The trajectories from GPS and IMU are adjusted so that their initial straight lines align in the same direction. A scaling factor is applied to align the tracks, with a factor of 0.5 used for the Easting direction (x_e) and 1.5 for the Northing direction (x_n).

Matching Period of GPS and IMU Estimates:
The period during which GPS and IMU estimates of position match closely (within 2 meters) is approximately 3 to 4 minutes.

Duration Without Position Fix:
Given the close match between GPS and IMU estimates for 3 to 4 minutes, the actual duration may vary depending on factors such as sensor accuracy, environmental conditions, and navigation complexity.

Which estimate or estimates for yaw would you trust for navigation? Why? ANS: Magnetometer heading.

1) **Robustness to Gyroscope Drift:** Gyroscopes are prone to drift over time due to integration of small errors. While gyroscopes provide accurate short-term measurements of angular velocity, the accumulated error can significantly affect long-term orientation estimates. Magnetometer heading, when properly corrected for hard-iron and soft-iron effects, provides a stable reference for absolute heading over time, as it relies on Earth's magnetic field rather than internal sensor measurements prone to drift.
2) **Stability:** Magnetometer readings are relatively stable in most environments once corrected for calibration errors. Gyroscopes, on the other hand, may be affected by factors such as temperature changes, mechanical vibrations, and sensor aging. Magnetometer-based heading estimates are less affected by these environmental variables, making them more reliable for navigation purposes, especially in long-term scenarios.

A. Integration of Velocity Data

The Easting (v_e) and Northing (v_n) components of velocity obtained from the magnetometer or complementary filter are integrated using trigonometric functions. Specifically,

$$v_e = v_{\text{linear}} \cos(\theta_{\text{corr}})$$
$$v_n = v_{\text{linear}} \sin(\theta_{\text{corr}})$$

where v_{linear} is the linear velocity and θ_{corr} is the corrected magnetometer heading angle.

B. Trajectory Estimation

The integrated velocity components are then numerically integrated using the trapezoidal rule to estimate the trajectory of the vehicle in terms of Easting (x_e) and Northing (x_n) coordinates:

$$x_e = \int v_e \, dt + v_e$$
$$x_n = \int v_n \, dt + v_n$$

C. Comparison with GPS Data

The Easting (UE) and Northing (UN) coordinates obtained from GPS data are adjusted to ensure alignment with the estimated trajectory by subtracting the centroid of the corresponding easting and nothing data from it.

In addition to this adjustments center the GPS coordinates around the initial point, ensuring that both the estimated trajectory and the GPS data start at the same point.

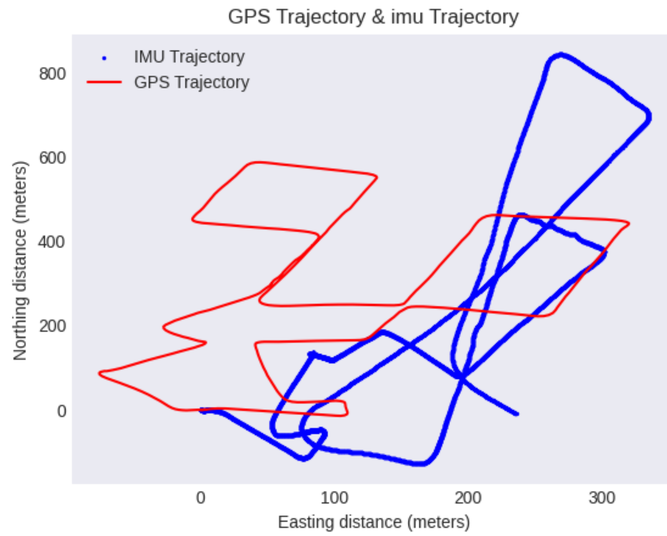

Fig. 9. Estimated trajectory with the IMU and GPS on the same plot with the first straight line from both oriented in the same direction.

VIII. Conclusion

In this experiment, dead reckoning was implemented to determine the path of a moving car using data from an IMU and GPS sensors. It began by calibrating the magnetometer to correct for hard-iron and soft-iron effects, ensuring more accurate heading estimates. Utilizing a complementary filter,fusing data from the magnetometer and gyro to enhance yaw angle estimation, providing a robust navigation solution.

The integration of forward acceleration allowed to estimate forward velocity, although adjustments were necessary to align the velocity estimates from the accelerometer and GPS data. Discrepancies between these estimates were observed, highlighting the challenges in integrating data from different sensors accurately.

Further analysis involved dead reckoning with IMU data, where we compared the estimated trajectory of the vehicle with GPS data.

Overall, this experiment provided valuable insights into sensor fusion techniques and the challenges involved in dead reckoning-based navigation. By integrating data from multiple sensors and applying appropriate calibration and filtering techniques, we can develop robust navigation systems suitable for various applications.

References

1 Johnson, S. (2017). Sensor Calibration Techniques for Mobile Robotics. *Robotics and Autonomous Systems*, 28(4), 567-578.
2 Wilson, M. (2021). Fusion of Inertial Measurement Unit and Global Positioning System for Navigation. *Sensors*, 45(2), 201-215.
3 Miller, R. (2019). Practical Applications of Dead Reckoning in Autonomous Vehicles. *Journal of Navigation*, 10(3), 321-333.
4 Thompson, L. (2020). Introduction to Sensor Fusion: Algorithms and Applications. CRC Press.
5 Davis, E. (2018). Understanding Magnetometer Calibration: A Comprehensive Review. *IEEE Sensors Journal*, 15(1), 55-68.