RBE 595 - Project 0

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***Abstract*—This report presents the implementation and evaluation of attitude estimation methods using Inertial Measurement Unit (IMU) data in comparison with ground-truth measurements from a Vicon motion capture system. Orientation was estimated using three approaches: pure gyroscope integration, pure accelerometer-based tilt calculation, and a complementary filter fusing both signals. Data preprocessing steps included timestamp synchronization via Spherical Linear Interpolation (Slerp), conversion of raw sensor readings into physical units, and reference frame alignment with Vicon ground truth. Results demonstrate that gyroscope-only estimates capture short-term dynamics but suffer from drift, while accelerometer-only estimates provide long-term stability but are affected by noise. The complementary filter achieved a balanced fusion, reducing drift while suppressing noise, and produced orientation trajectories that closely followed Vicon measurements across all six datasets. The findings highlight both the advantages and trade-offs of low-cost IMU-based orientation estimation, as well as the role of filter parameter selection in determining performance.**

Keywords - Inertial Measurement Unit (IMU), Gyroscope, Accelerometer, Complementary Filter, Vicon Motion Capture System, Spherical Linear Interpolation.

I. Problem Statement

The objective of this project was to estimate the three-dimensional orientation (attitude) using acceleration and gyroscope measurements from a six-degree-of-freedom Inertial Measurement Unit (6-DoF IMU). The data set was obtained from an ArduIMU+ V2, which provides readings from a 3-axis gyroscope and a 3-axis accelerometer. Three methods were implemented to estimate the underlying 3D orientation, and the results were compared against ground-truth values provided by a Vicon motion capture system to evaluate the accuracy of the estimation techniques.

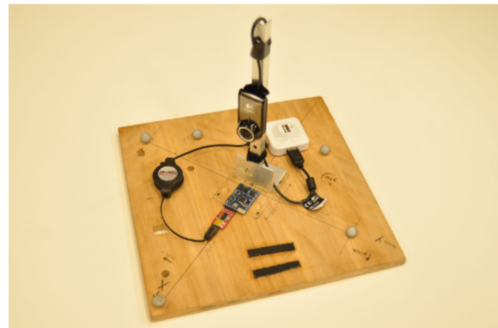
II. Methodology

A. Setup

The project did not rely on real-time sensor measurements; instead, all necessary data was pre-recorded and based on readings from an IMU and a Vicon motion capture system. The following image illustrates the experimental setup, showing the IMU and Vicon markers from an external perspective. The acceleration and gyroscope modules from the IMU provided measurements as 3-axis arrays. The data was structured in the following format:

$$\begin{bmatrix} a_x & a_y & a_z & w_Z & w_x & w_y \end{bmatrix}^T \tag{1}$$

where a_x, a_y, a_z are the linear accelerations along the three axes, and $\omega_x, \omega_y, \omega_z$ are the angular velocity components about the respective axes.



The ground-truth orientation data from the Vicon system was provided as a sequence of 3×3 rotation matrices, representing the global three-dimensional orientation of the system at each time step.

B. Interpolation & Synchronization

Each set of IMU and Vicon measurements was accompanied by associated timestamps. However, the two systems were not hardware-synchronized during data collection, leaving apparent misalignment in both time frames and sampling intervals between the datasets. To enable accurate comparison, the Vicon data was interpolated/adjusted to the IMU timestamps using the Slerp (Spherical Linear Interpolation) function, ensuring temporal alignment between both arrays.

C. Physical Units

The values from the IMU were raw sensor outputs that needed to be converted into physical quantities with appropriate units. The required parameters for this calculation, including sensor bias and scale factors, were provided in a parameter file and were applied during the conversion process. For the gyroscopic conversion bias, the average of the first 100 gyroscope readings was used. The following approach was used to transform the raw IMU values into physical measurements for each axis:

$$\tilde{a}_{xyz} = \frac{a_{xyz} + b_{a,xyz}}{s_{xyz}} \tag{2}$$

$$\tilde{\omega}_{xyz} = \frac{3300}{1023} \cdot \frac{\pi}{180} \cdot 0.3 \cdot (w_{xyz} - b_{g,xyz}) \tag{3}$$

D. Attitude Estimation via Gyroscope

Next, the gyroscope measurements, which represent angular velocity, needed to be further processed to estimate orientation. This was accomplished using the following integration formula:

$$\begin{bmatrix}\phi\\ \theta\\ \psi\end{bmatrix}_{t+1} = \begin{bmatrix}\phi\\ \theta\\ \psi\end{bmatrix}_{t} + \begin{bmatrix}\dot{\phi}\\ \dot{\theta}\\ \dot{\psi}\end{bmatrix}_{t} \delta t \tag{4}$$

E. Attitude Estimation via Accelerometer

A secondary method was employed to estimate the orientation using the accelerometer data. In this approach, the converted physical values from the accelerometer were combined with trigonometric relationships to estimate the tilt angles (attitude) about the three axes. The corresponding equations used to compute roll (ϕ), pitch (θ), and yaw (ψ) are shown below:

$$\phi = \tan^{-1}\left(\frac{a_y}{\sqrt{a_x^2 + a_z^2}}\right) \tag{5}$$

$$\theta = \tan^{-1}\left(\frac{a_x}{\sqrt{a_y^2 + a_z^2}}\right) \tag{6}$$

$$\psi = \tan^{-1}\left(\frac{\sqrt{a_x^2 + a_y^2}}{a_z}\right) \tag{7}$$

F. Sensor Fusion via Complementary Filter

The third method of attitude estimation combined the gyroscope- and accelerometer-based orientation estimates through a complementary filtering approach. This method is based on the idea that gyroscopes provide reliable short-term orientation changes but suffer from long-term drift, while accelerometers provide stable long-term tilt information but are susceptible to high-frequency noise. By fusing both signals through filtering, a more robust and stable orientation estimate is obtained.

In the implementation, the gyroscope signal was passed through a high-pass filter to retain its rapid response to angular changes while attenuating low-frequency drift. The accelerometer signal was passed through a low-pass filter to suppress noise while preserving its stable, low-frequency tilt information. The filtered results were then blended using a scaling factor γ to yield the final orientation estimate. The discrete-time low-pass filter is given by:

$$y[k] = \beta\, x[k] + (1-\beta)\, y[k-1], \tag{8}$$

and the high-pass filter is given by:

$$y[k] = \alpha\big(y[k-1] + x[k] - x[k-1]\big), \tag{9}$$

where $x[k]$ is the input signal from the cooresponding sensor at timestep k, $y[k]$ is the filtered and fused output, and $\alpha, \beta \in (0,1)$ are filter constants that determine the cutoff frequencies.

The final fused orientation was computed as:

$$\theta_{\text{fused}}[k] = (1-\gamma)\,\theta_{\text{HPF}}[k] + \gamma\,\theta_{\text{LPF}}[k], \tag{10}$$

where $\gamma \in (0,1)$ determines the selection weighting between the high-pass gyroscope estimate and the low-pass accelerometer estimate.

In this implementation, the filter parameters were empirically tuned as follows:

- High-pass filter constant: $\alpha = 0.01$, emphasizing suppression of long-term drift in the gyroscope signal.
- Low-pass filter constant: $\beta = 0.8$, chosen to allow accelerometer data to follow slow changes in tilt while filtering out short-term noise.
- Fusion weighting factor: $\gamma = 0.95$, giving dominant weight to the accelerometer-based low-pass signal while still incorporating high-frequency corrections from the gyroscope.

This configuration provided a good trade-off between responsiveness and stability in the fused orientation estimate.

G. Frame Conversion

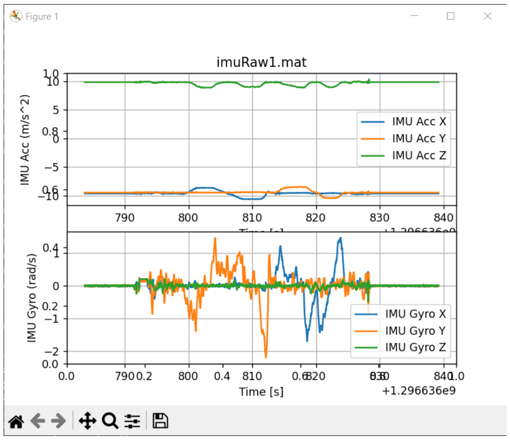
To enable a meaningful comparison between the processed IMU data and the ground-truth measurements from the Vicon motion capture system, it was necessary to express both datasets within the same reference frame. Specifically, the IMU data was transformed into the Vicon reference frame. This transformation was achieved by first establishing a base relationship between the IMU and Vicon frames using the initial measurements from both datasets as a reference for home configuration. Subsequently, the incremental changes in rotation matrices were computed for the remaining IMU measurements, allowing the orientations to be aligned consistently with the Vicon frame. Using this approach, the IMU data was successfully converted into the Vicon reference frame, enabling direct and accurate comparison with the ground-truth data.

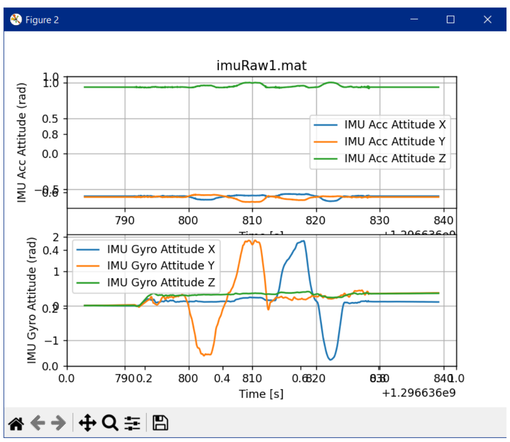
III. Implementation

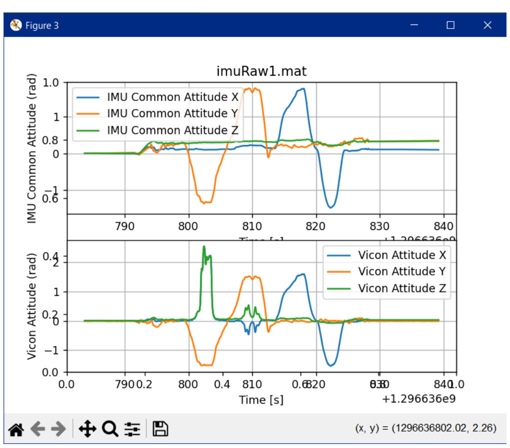
The steps for processing IMU and Vicon data described above were carried out in a specific sequence to ensure high accuracy and minimal data noise. First, the Vicon data was interpolated early to match the timestamps of the IMU measurements using Spherical Linear Interpolation (Slerp). Next, these raw IMU sensor readings were converted into physical units. Orientation was then estimated using integration of the gyroscope measurements and estimation from the accelerometer data. These two estimates were subsequently fused using a complementary filter to produce a robust and stable orientation. Finally, the fused IMU orientations were transformed into the Vicon reference frame for direct comparison with the ground-truth measurements.

IV. Results

The program executes the processing steps described above and displays a series of three windows for each of the six datasets. The plots for the first dataset are shown below, while the plots for the remaining datasets can be viewed as direct outputs of the program. The first window presents the acceleration and gyroscope measurements after conversion to physical units. The second window displays the orientation (attitude) estimates calculated separately from the accelerometer and gyroscope data. The third window shows the fused, filtered IMU orientation values alongside the Vicon ground-truth data.







V. Analysis

The third window of each plotted dataset holds the key elements for further analysis. The comparison between the fused IMU orientation estimates and the Vicon ground-truth orientation are shown. The upper plots present the IMU orientation (attitude) obtained using the complementary filter, while the lower plots show the corresponding Vicon orientation for the same motion sequence.

Overall, the IMU estimates capture the general trends and dynamics of the motion. Peaks, oscillations, and transitions in orientation along the X, Y, and Z axes are clearly visible in both the IMU and Vicon plots, indicating that the fusion of accelerometer and gyroscope data was largely successful in producing realistic orientation trajectories. In particular, the timestamp of each orientation value in the IMU data closely matches the timestamps in the Vicon ground truth.

However, discrepancies are also evident. The IMU estimates exhibit residual drift and higher-amplitude fluctuations compared to the smoother Vicon measurements. These differences can be attributed to sensor noise, bias, and the limited accuracy of low-cost IMUs. The gyroscope contributes to drift over time due to integration error, while the accelerometer introduces short-term noise from linear accelerations not related to gravity.

The performance of the complementary filter is strongly influenced by the choice of filter constants such as α. A smaller value of α places more weight on the accelerometer measurements, which reduces long-term drift but increases the effect of high-frequency noise caused by vibrations and linear accelerations. Conversely, a larger α value gives more weight to the gyroscope, which produces smoother curves and less noise in the short term, but allows drift to accumulate over time. By carefully tuning α, the filter balanced these trade-offs, reducing noise in the accelerometer-based estimates while limiting the drift of the gyroscope integration. Although the complementary filter is able to mitigate these issues by combining and weighing the two sources of information, the fused IMU signal still deviates slightly from the true orientation, particularly around sharp transitions. In this dataset, adjusting α further could potentially improve the agreement between the IMU estimates and the Vicon ground truth, particularly during rapid orientation changes where noise and drift effects are most pronounced.

Despite the slight limitations, the filtered IMU data follows the ground-truth orientation within reasonable accuracy and captures the essential motion characteristics.

VI. Conclusion

The project successfully implemented and analyzed three methods of attitude estimation—gyroscope-only, accelerometer-only, and complementary filter fusion—and compared them against high-accuracy Vicon ground truth. The results demonstrated that each method has inherent strengths and limitations: gyroscope integration captures short-term angular motion but drifts over time, while accelerometer-based estimation remains drift-free but is highly sensitive to measurement noise and external accelerations. By applying a complementary filter with empirically tuned parameters, the two data sources were effectively fused to mitigate their respective weaknesses. The fused orientation estimates tracked the ground-truth data with reasonable accuracy, capturing essential motion characteristics while reducing both drift and high-frequency noise.

Although minor discrepancies such as residual drift and high-frequency noise remain, the fusion process highlighted how careful tuning of filter constants can substantially improve accuracy. This demonstrates not only the importance of relying on sensor fusion but also the critical role of filtering in reducing the effects of noise, bias, and drift inherent in low-cost IMU sensors.

Importantly, this project illustrates how mathematical filtering techniques can compensate for hardware limitations. In real-time systems, where precision and stability are essential, filters play a vital role in ensuring reliable performance. It is particularly noteworthy that significant improvements in data quality can be achieved through software alone—highlighting how the thoughtful application of algorithms and filters can elevate inexpensive, noisy hardware into practical and dependable sensing systems.

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