DEVELOPMENT OF A HIGH-ACCURACY ALIGNMENT SOLUTION USING A LOW-PRECISION INERTIAL MEASUREMENT SENSOR (ALIGN)
ROKETSAN

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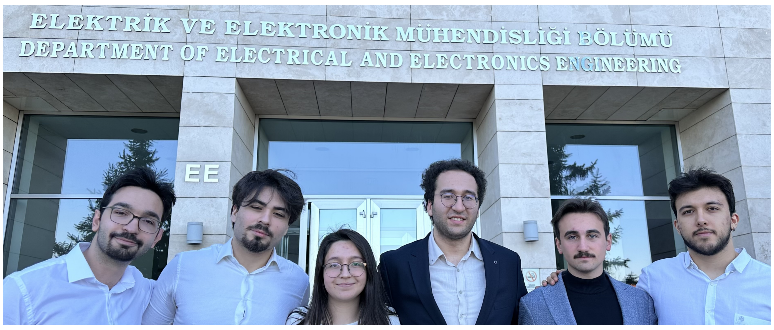

Abstract. A sensitive initial-alignment solution is essential during flight, since it underpins the launch vehicle's orientation, position, and velocity calculations. Our project estimates this initial attitude by fusing an Inertial Measurement Unit (IMU) with an auxiliary magnetometer. We introduce a two-stage alignment: a coarse step that combines expected prior attitude with a Gauss–Newton optimization, followed by a fine step using a quaternion-based Extended Kalman Filter equipped with dynamic covariance updates. To demonstrate its practicality, we validate our software algorithm in hardware by driving known IMU-magnetometer rotations through Arduino into MATLAB and observing convergence. With this fusion strategy, our aim is to achieve an error of less than 0.1 degrees in all axes.

PROJECT DESCRIPTION

Initial alignment is the process of estimating the orientation of a launch vehicle prior to launch. The determined orientation is used as a basis for the calculations of orientation and position estimations during flight [1]. Thus, the need to estimate the initial orientation accurately arises, which motivates our project.

Measurements to estimate the attitude are done using inertial measurement units (IMU), which come in four grades: industrial, tactical, navigation, and strategic, increasing in sensitivity and price in the given order. Roketsan aimed to obtain an estimation accurate to 0.1 degrees in all axes, while using low-end tactical-grade IMUs and possibly other additional sensors, prioritizing effectiveness and cost. Upon successful completion of the project, Roketsan will be the owner and the target user of the project, although they may opt to share it with other parties.

There are a multitude of existing works on the initial alignment problem. However, there are no works that can capture the desired accuracy using tactical-grade IMUs, as navigation or strategic-grade IMUs are more commonly used with more demanding accuracy goals. Most current practices with low-sensitivity sensors achieve an accuracy of around 0.5 to 0.6 degrees, according to our mentors. Other implementations are either confidential and/or patented, or do not meet either of the accuracy or cost criteria. Similar works include NASA's SLS Inertial Navigation System, which includes Gyrocompass Alignment [2]. This system includes gyrocompasses and aims to navigate the entire movement of a launch vehicle, differentiating it from our project, as we are focused only on the initialization of the vehicle. A patent belongs to Ningbo Tianqing Aerospace Technology Co., for their project that aims to develop an autonomous initial alignment for rapid-response rockets [3]. However, in its relevant paper, the error margin to be achieved is not explicitly stated, and therefore, a direct comparison with our project is difficult. A novel and possibly patentable aspect of our project is the development of a new alignment algorithm that uses innovative approaches.

In the big picture, we are using two IMUs and two magnetometers. Two Arduino UNO cards are utilized since identical sensors have the same Inter-Integrated Circuit (I^2C) addresses. The IMU and magnetometer share the same I^2C bus. The sensor readings are passed to the computer with the Universal Serial Bus (USB) 3.0 protocol, and our algorithm, consisting of coarse and fine alignment, gives us an estimation of orientation in Euler angles.

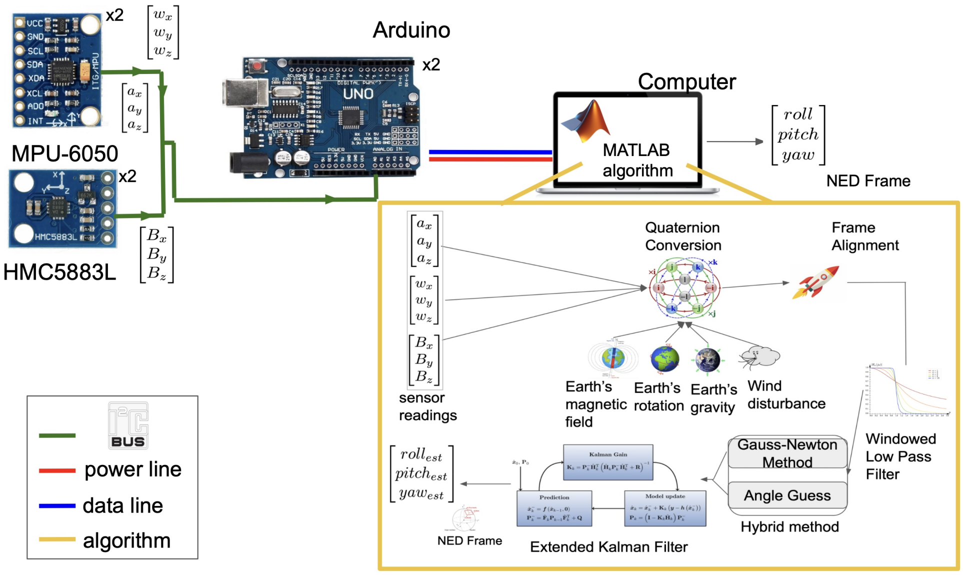

FIGURE 1. The Big Picture

MILESTONES

1. Research and Requirement Finalization: This milestone identifies optimal alignment and estimation strategies for tactical-grade sensors to meet the 0.1° accuracy requirement. Success is defined by completing a literature review, sensor evaluation, and finalizing system requirements with academic and industry mentor input.

2. Software Sensor Modeling and Simulation Framework: The goal is to create accurate MATLAB models of the sensors under real-world conditions to test the algorithm before hardware integration. This milestone is successful when simulated outputs match expected behavior, including noise, bias, and disturbances.

3. Coarse Alignment Algorithm Development: A hybrid coarse alignment approach is developed to provide reliable orientation using a weighted combination of Gauss-Newton and prior orientation estimates. Success is measured by the algorithm maintaining error margins within acceptable limits at various test angles.

4. Quaternion-Based Extended Kalman Filter Implementation: This milestone aims to develop a quaternion-based extended Kalman filter (EKF) for precise orientation estimation without gimbal lock and robust noise suppression. This milestone is successful when orientation errors on all three axes stay below 0.1° in simulation results.

5. Consistency Metrics and Dynamic Covariance Tuning: The consistency metrics Normalized Estimation Error Squared (NEES) and Normalized Innovation Squared (NIS) are used to monitor and enhance filter accuracy by dynamically adjusting noise covariances. Success is achieved when both NEES and NIS values consistently stay within their chi-squared bounds.

6. Multiple IMU and Magnetometer Integration: To enhance accuracy and suppress noise, a dual-sensor setup is implemented with opposing sensor orientations and real-time fusion using a microcontroller. This step succeeds if the multiple sensor configuration shows improved convergence and reduced orientation error compared to a single-sensor setup.

7. Algorithm Refinement and Error Reduction: The goal of this milestone is to refine the alignment algorithm to improve its accuracy, particularly in challenging cases such as near-vertical orientations. It is considered successful if the orientation error remains below $0.1°$ in both simulation and hardware.

DESIGN DESCRIPTION

For Milestone 1, the following has been completed:

Research Completion: Upon extensive literary research, different alignment algorithms were considered, ranging from the basic Kalman filter, the EKF, to the Madgwick filter [4],[5],[6]. For its efficiency and capability to adapt to nonlinear processes, such as vibrations caused by wind, EKF was considered the most viable option among all the algorithms. Similarly, to reduce the alignment error, an iterative algorithm, the Gauss-Newton method, is used, which allows the EKF to increase the accuracy of the observed attitude.

For Milestone 2, the following items have been completed:

Wind Modeling: To realistically model the behavior of the vibratory effects of wind on the body of the launch vehicle, the orientation of the ground truth was distorted through additive Gaussian noise. Since natural processes such as wind have slow-changing characteristics, the Gaussian noise was transformed into pink noise via low-pass filtering [7].

Sensor Model Implementation: For the tactical grade sensor model implementation, the provided specifications of bias, random walk error, axial misalignment, in-run bias stability (IRBS), and bandwidth were used to simulate the IMU, MPU6050, and magnetometer, HMC5883L. After the model implementation was complete, the wind-corrupted orientation information was input to the sensor models at every time instance to generate the sensor readings.

Windowed Low Pass Filter (W-LPF): Since the low-end tactical grade sensors possess high levels of random walk error, an LPF was implemented to get rid of the high frequency noise. To avoid accidentally filtering sudden changes in the orientation along with the noise, a W-LPF was applied only to the most recent sensor readings. The filter cut-off and the window length was chosen based on the bandwidth of the sensors.

Quaternions: To prevent possible orientation problems in Euler angles during the calculation of the attitude, also referred to as "Gimbal Lock", quaternions, which are 4-dimensional arrays, were used to present the overall attitude estimation algorithm.

For Milestone 3, the following item has been completed:

Coarse Alignment: Attitude alignment can be separated into coarse and fine alignment. For the coarse alignment algorithm, the Gauss-Newton method and expected prior attitude information were used. Among these methods, the Gauss-Newton method refers to an optimization algorithm that aims to find the attitude of the body frame by minimizing the error between the Earth's North-East-Down (NED) frame and the body frame using the filtered magnetometer and accelerometer measurements. On the other hand, expected prior attitude information is used as a correction factor, utilizing prior information such as an upright launch vehicle pitch angle close to 90 degrees. The coarse alignment method uses these methods as a weighted linear combination to estimate the attitude more accurately.

For Milestone 4, the following item has been completed:

Fine Alignment: For the fine alignment method a Quaternion based EKF was used. The EKF filter essentially utilized the information obtained from gyroscope readings and computed the residual between the coarse alignment algorithm and predictions in an iterative manner.

For Milestone 5, the following items have been completed:

Dynamic Covariance Update: To assess the consistency of the EKF and potentially improve the performance of the attitude estimation, two different consistency metrics: NEES and NIS. The results of the consistency metrics were used to change the noise covariance matrices of the EKF to provide a stronger convergence.

Direction Cosine Matrix (DCM) Error: Since orientation in 3-dimensional space is not uniquely defined by the Euler angles, the difference between the estimated and true Euler angles is inappropriate as an error metric. Instead, the estimated quaternions from the EKF are transformed into a rotation matrix, which describes an attitude in the NED frame, called the DCM, along with the ground truth. The inverse of the estimated DCM and true DCM is used to recover the DCM of the attitude error, which is then transformed into Euler angles for interpretability.

For Milestone 6, the following items have been completed:

In the hardware setup, the sensors, in opposite directions along the x and y axes to minimize environmental interference, were placed atop the Stewart platform for measurement. Magnetometers were calibrated using Arduino before being placed in the system. This calibration method is based on finding the scale factor and offset values. Finally, the orientation of the hardware setup is found with the algorithm developed in the software implementation.

The following tools have been used to complete milestone 6:

TABLE 1. Used Tools and Their Purposes

Purpose	**Model**
Software Algorithm	MATLAB
IMU	MPU-6050
Magnetometer	HMC5883L
Microprocessor	Arduino UNO

RESULTS AND PERFORMANCE EVALUATION

To validate our simulation, we tested a range of input orientations, emphasizing pitch angles near 90°, which correspond to the vehicle's expected pre-launch attitude. We computed the mean and standard deviation of the orientation errors after the estimator converged (typically taking only a few seconds), so our statistics use only the second half of each run.

At 90 ° pitch, where a singularity might arise, the roll error stayed around 0.7°, while pitch error was around 1.6° and yaw errors hovered near 0°. We then repeated the same analysis at other pitch-yaw-roll angles and observed generally better performance across almost all nonsingularity angles. These results show that our algorithm handles potential singularity angles robustly and performs consistently well across other orientations.

Although we cannot directly compare our results with other systems, we can conclude that yaw angle estimation has been improved by using a magnetometer. Thus, it can be said that utilizing a coarse and a fine alignment has improved our accuracy significantly.

TABLE 2. Error means for various input orientations

Input Orientation [yaw, pitch, roll]	Roll Error Mean	Pitch Error Mean	Yaw Error Mean
[0,0,0]	-0.41	-0.32	-1.027
[10,88,4]	0.34	-0.36	0.69
[0,90,0]	0.77	-1.6	-0.00053
[30,70,20]	0.25	-0.39	1.17
[70,85,30]	0.4581	-0.1013	3.1529

TABLE 3. Error standard deviations for various input orientations

Input Orientation [yaw, pitch, roll]	Roll Error Std Dev	Pitch Error Std Dev	Yaw Error Std Dev
[0,0,0]	0.16	0.174	0.19
[10,88,4]	0.10	0.139	0.22
[0,90,0]	0.19	0.24	0.22
[30,70,20]	0.11	0.15	0.24
[70,85,30]	0.1679	0.0545	0.26

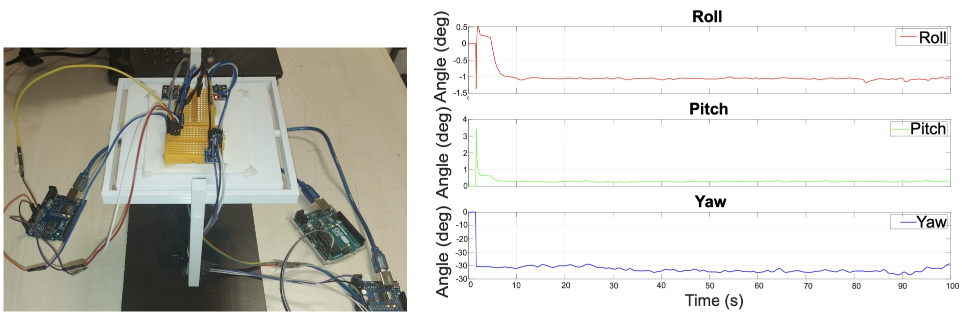

FIGURE 2. (a) Hardware Setup (b) Estimated Orientation

Since we don't have an external ground truth in our hardware setup. In the hardware tests, convergence is verified by physically rotating the platform through a series of known angles while both sensors remain active. During each rotation step, the calibrated IMU and magnetometer stream raw measurements via Arduino to MATLAB, where our attitude-alignment algorithm ingests the data, computes the estimated orientation at every time increment, and plots the convergence behavior. Moreover, to confirm stability by holding the platform static after each rotation and observing that the estimated attitude remains steady. Finally, we observed that a differentially mounted, multi-sensor arrangement converges both more quickly and more reliably than any single-sensor configuration that we have tested before.

CONCLUSION AND FUTURE DIRECTIONS

This project set out to provide Roketsan with a high-accuracy initial alignment solution using tactical-grade IMUs and magnetometers. Combining a Gauss–Newton-based coarse alignment with a quaternion-based Extended Kalman Filter for fine alignment, and dynamically tuning the filter's covariances via NEES/NIS metrics, we achieved substantial improvements over existing methods. Although the strict 0.1° error target was not consistently met across all axes and orientations, our results demonstrated significantly better accuracy than current in-use algorithms.

Looking forward, future improvements can focus on estimating and compensating for sensor biases in real time, reducing steady-state error, and enhancing filter consistency. Finally, exploring alternative filtering frameworks, such as the Unscented Kalman Filter or optimization-based methods, could also yield further gains.

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BEHIND THE SCENES