RESPONSE TIME IN INERTIAL MEASUREMENT UNIT CONTROL ALGORITHMS

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Abstract. The Inertial Measurement Unit (IMU) [1] is a cornerstone technology in various fields, ranging from aerospace to consumer electronics, where accurate motion tracking is paramount. Central to the effectiveness of an IMU is the quality of data processing, particularly in the context of filtering techniques. This study compares two filtering methods: Complementary Filters and Kalman Filters, in their application to IMU data processing. Complementary Filters, known for their simplicity and efficiency, contrast with the more complex but potentially more accurate Kalman Filters. Our investigation delves into the underpinnings of each filter, followed by a practical analysis of their performance in real-world IMU applications. We comprehensively compare these filters in terms of accuracy, computational efficiency, and ease of implementation. This research offers valuable insights for practitioners and researchers in selecting the most suitable filtering approach for specific IMU-based applications, enhancing the overall quality of motion sensing and analysis.

Key words: IMU, Complementary Filter, Kalman Filter, Motion Tracking Accuracy

1. Introduction

The growing popularity of underwater remotely operated vehicles (ROVs) [2] in cost-effective applications and academic research is a testament to their acessible and economical design, making their operability a subject of vibrant discussion. One of the traditional challenges in ROV systems is state estimation, a topic extensively explored in literature, particularly focusing on various filtering techniques to estimate parameters exactly. Advanced filtering methods, like the particle filter, are known for their computational intensity and are typically reserved for powerful processors on the mainboard.

Two prevalent methods in this realm are the Kalman filter [3] and the Complementary filter [4], both favored for their efficient frequency filtering capabilities in linear systems. The Kalman filter has been a focal point in numerous studies related to underwater control systems. For attitude estimation in underwater vehicles, known studies have adapted the standard Kalman filter to refine measurement updates. These adaptations often involve the multiplicative extended Kalman filter, which integrates data from accelerometers, gyroscopes, and depth sensors. Researchers have also proposed employing the Kalman filter in conjunction with a six-axis attitude determination algorithm as the observer. While this method is efficient, it demands significant computational resources. Therefore, it is convenient to track motion with the help of small inertial/magnetic sensors.

Despite its effectiveness, the robust application of the Kalman filter in underwater environments presents challenges. In response, recent work has seen a shift towards the issue of complementary filters for high-quality attitude extraction and gyro bias estimation. This approach allows for filters to be formulated explicitly in quaternion form, facilitating straightforward implementation and enhancing the operational proficiency of underwater ROVs..

2. Drawbacks

Traditional pose estimation combines accelerometer and magnetometer measurements to derive the final pitch, roll, and yaw angles. However, without filtering, this method often results in significant noise and inaccuracies in the recorded poses, particularly in the yaw angle (as magnetometer data provides absolute orientation) [5]. This introduces substantial challenges in controlling ROVs.

Complementary filtering addresses these issues by weighted fusion of accelerometer and gyroscope measurements, reducing drift errors in pose estimation. Moreover, the computational complexity of complementary filtering is significantly lower than Kalman filtering, providing substantial assistance in real-time control of ROV poses.

3. Goal

The goal is to study complementary filtering techniques mitigating noise and inaccuracies, particularly in yaw angle determination, which significantly impact the control of ROVs.

4. Comparison between Kalman filter and complementary filter

Deploying an accelerometer and gyroscope and using complementary filtering, can enhance the accuracy and reliability of real-time pose estimation [6] while reducing computational complexity compared to conventional methods. Ultimately, this research seeks to improve the effectiveness and efficiency of ROV control systems, enabling more precise maneuvering and navigation in various underwater environments.

Kalman Filtering is an optimum approach that combines state estimations with observational data. The Kalman Filter is inherent in the minimization of system noise and uncertainty while providing generally accurate posture estimates [7]. However, its implementation is relatively difficult, incorporating concepts such as state space models and covariance matrices, and it requires a large amount of processing resources. This complexity may make it less appropriate for usage in resource-constrained embedded devices.

Comparison Aspect	Kalman Filtering	Complementary Filtering
Complexity	High	Low
Computational Overhead	Substantial	Minimal
Implementation Difficulty	Complex	Straightforward
Adaptability to Dynamic Environments	Moderately Good	Limited
Attitude Estimation Accuracy	High	Moderate
Resource Consumption	Considerable	Low
Suitability for High-Dynamic Movements	Excellent	Limited
Real-Time Performance	Relatively Slow	Relatively Fast
Multi-Sensor Fusion	Applicable	Applicable

On the other hand, Complementary Filtering provides a simple and effective way of estimating pose. It accomplishes this by combining data from accelerometers and gyroscopes, reducing drift in pose estimation. Complementary Filtering has several advantages, including its simplicity of implementation and minimal computational load, making it ideal for applications requiring excellent real-time performance. However, it may struggle in dynamic situations or during quick motions due to accumulated mistakes, potentially resulting in unstable pose estimates.

Comparison Aspect	Accelerometer	Gyroscope
Sensitivity to High-Frequency Vibrational Noise	Sensitive	Insensitive
Low-Frequency Attitude Drift	Stable	Drifts
Resistance to High-Frequency Interference	Weaker	Stronger
Resistance to Low-Frequency Interference	Stronger	Weaker

5. Implementation and Derivation of Complementary Filtering

Complementary Filtering is a widely used approach for attitude assessment that depends on the data fusion of two sensors: the accelerometer and the gyroscope [4]. The key to this strategy resides in optimizing the strengths of these sensors to improve the accuracy and reliability of attitude assessment.

Processing Accelerometer Data:

The accelerometer detects the deviation angle between the acceleration and gravitational acceleration vectors to determine the object's tilt. However, accelerometers detect gravity-induced acceleration, which can interfere with actual tilt measurements. As a result, the accelerometer signal must be adjusted to account for gravitational acceleration. Typically, a low-pass filter reduces high-frequency noise created by mechanical vibrations. After filtering, the data better captures the object's tilt.

Processing Gyroscope Data:

The gyroscope is designed to measure an object's angular velocity or speed of rotation. While gyroscopes are sensitive and precise in detecting rotational movements, their measurements can become inaccurate with time, causing drift in attitude calculation. The gyroscope's angular velocity data is coupled with the accelerometer's tilt information to minimize drift. This fusion is based on the complementarity concept, in which the outputs of both sensors are combined using a weighted average, thereby complementing each other's power.

Derivation of the Complementary Filter Formula:

For the gyroscope measurements gx, gy, gz, and the error terms e, ey, ez, along with their integral components $exInt$, $eyInt$, $ezInt$, the derivation of the Complementary Filter can be expressed as follows:

$$gx = \alpha \cdot gx + (1-\alpha) \cdot (Kp \cdot ex + exInt)$$
$$gy = \alpha \cdot gy + (1-\alpha) \cdot (Kp \cdot ey + eyInt)$$
$$gz = \alpha \cdot gz + (1-\alpha) \cdot (Kp \cdot ez + ezInt)$$

- The alpha (α) value typically ranges between 0.98 and 0.99, adjustable based on the specific scenario and hardware characteristics.

- Kp represents the proportional gain, used to adjust the influence of the error term on the gyroscope measurements.

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- The error terms ex, ey, ez represent the cross-product of the estimated direction of gravity and the accelerometer measurements.

- The component $exInt$, $eyInt$, $ezInt$ are the integrals of the error terms.

Overall Implementation Process:

a) Input Conversion: Convert angular velocity to radians per second.

$$gx = gx \times 0.01745329$$
$$gy = gy \times 0.01745329$$
$$gz = gz \times 0.01745329$$

b) Normalization of Accelerometer Measurements:

$$norm = \sqrt{ax^2 + ay^2 + az^2}$$

Compute and normalize the magnitude of the accelerometer measurements.

$$ax = \frac{ax}{norm}, ay = \frac{ay}{norm}, az = \frac{az}{norm}$$

c) Estimation of Gravity Direction: Estimate the direction of gravity based on the current quaternion.

$$vx = 2.0 \times (q1 \times q3 - q0 \times q2)$$
$$vy = 2.0 \times (q0 \times q1 + q2 \times q3)$$
$$vz = q0^2 - q1^2 - q2^2 + q3^2$$

d) Calculation of Error Terms: Define error terms as the cross-product of the estimated gravity direction and accelerometer measurements.

$$ex = ay \times vz - az \times vy$$
$$ey = az \times vx - ax \times vz$$
$$ez = ax \times vy - ay \times vx$$

e) Integration of Error Terms: Integrate the error terms.

$$exInt = exInt + ex \times \mathrm{Ki} \times \mathrm{dt}$$
$$eyInt = eyInt + ey \times \mathrm{Ki} \times \mathrm{dt}$$
$$ezInt = ezInt + ez \times \mathrm{Ki} \times \mathrm{dt}$$

f) Adjustment of Gyroscope Measurements: Adjust the gyroscope measurements, applying the Complementary Filter to each axis.

$$gx = \alpha \cdot gx + (1 - \alpha) \cdot (Kp \cdot ex + exInt)$$
$$gy = \alpha \cdot gy + (1 - \alpha) \cdot (Kp \cdot ey + eyInt)$$
$$gz = \alpha \cdot gz + (1 - \alpha) \cdot (Kp\, ez + ezInt)$$

g) Quaternion Integration Update: Update the quaternion using the angular velocity after Complementary Filtering.

h) Quaternion Normalization: Normalize the quaternion.

i) Calculation of Euler Angles: Compute the Euler angles based on the updated quaternion.

$$pitch = \mathrm{asin}(-2 \times q1 \times q3 + 2 \times q0 \times q2) \times 57.3$$
$$roll = \mathrm{atan}\,2(2 \times q2 \times q3 + 2 \times q0 \times q1, -2 \times q1 \times q1 - 2 \times q2 \times q2 + 1) \times 57.3$$
$$yaw = atan\,2(2 \times (q1 \times q2 + q0 \times q3), q0^2 + q1^2 - q2^2 - q3^2) \times 57.3$$

Through this process, Complementary Filtering effectively combines information from the accelerometer and gyroscope, providing a relatively accurate attitude estimation.

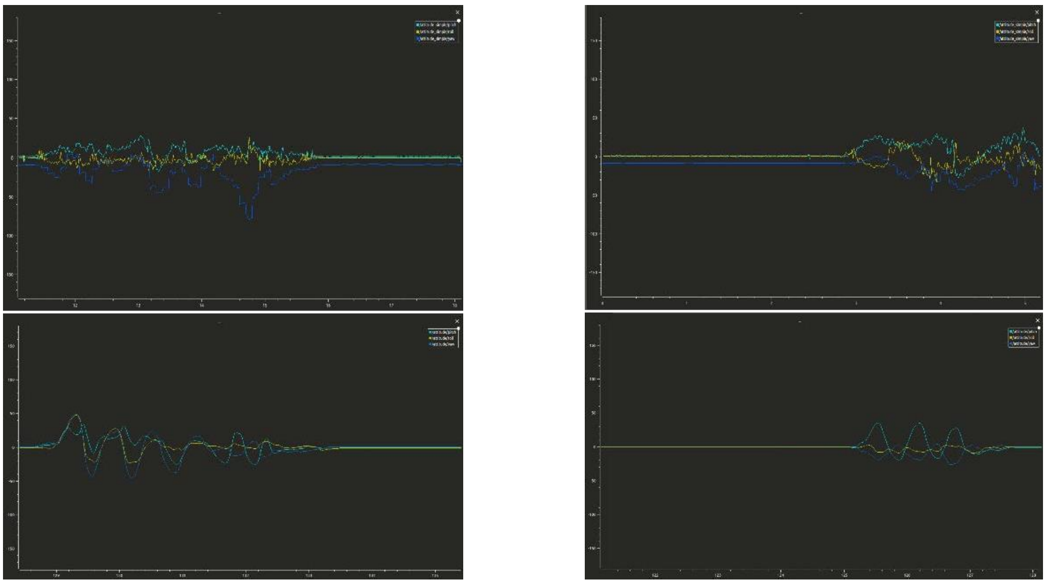

Fig. 1. Results of comparative analysis

In the conducted research, two experimental setups (Fig.1) were rigorously designed to contrast the performance of the tilt-compensated magnetometer-based yaw angle calculation method against the attitude estimation achieved through a complementary filter algorithm.

6. Conclusions

1. The conducted analysis of the Inertial Measurement Unit has confirmed that data processing quality depends on applied filtering techniques. There were studied and compared 2 filtering methods: Complementary Filters and Kalman Filters.

2. The comparative analysis of 2 experimental setups revealed that the complementary filter algorithm exhibited lower noise levels and a higher synchronization rate in attitude computation. Notably, the yaw angle derived from the magnetometer reflects an absolute position, inherently preventing the initialization of the yaw value at zero. This characteristic imposes significant limitations on the closed-loop control systems of remotely operated vehicles, due to the inherent inability to reset or calibrate the yaw orientation at the start of an operation.

3. In contrast, the complementary filter approach generates posture information relative to the position at startup, adjusting dynamically to changes in orientation. This adaptability ensures a more robust response to irregular alterations in the IMU's operational environment, delivering stable posture signals with significantly reduced noise. Furthermore, the complementary filter demonstrated superior recovery performance following disturbances, underscoring its efficacy in enhancing the precision and reliability of posture estimation in dynamic and unpredictable conditions.

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8. Mutual claims of authors

The authors declare the absence of any financial or other potential conflict related to the work.

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