A Data Driven Toggling Gain Complementary Filtering Approach for Orientation Estimation

Network and Data Analysis Group
Samnun Azfar - 200041130
Ramisa Zaman Audhi - 200041131
Mir Md Inzamam - 200041240

Supervised by
Abu Raihan Mostofa Kamal
Professor
Department of CSE
Islamic University of Technology

Co-supervised by
Mohammad Ishrak Abedin
Lecturer
Department of CSE
Islamic University of Technology

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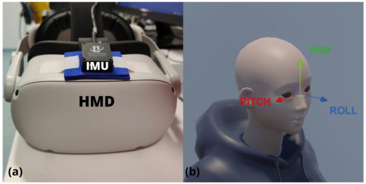
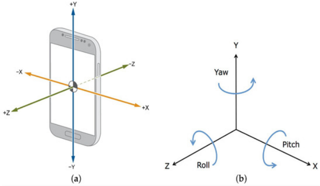
Introduction

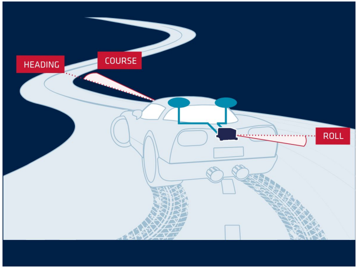
Orientation Algorithms in Real World Applications



VR Head-mount

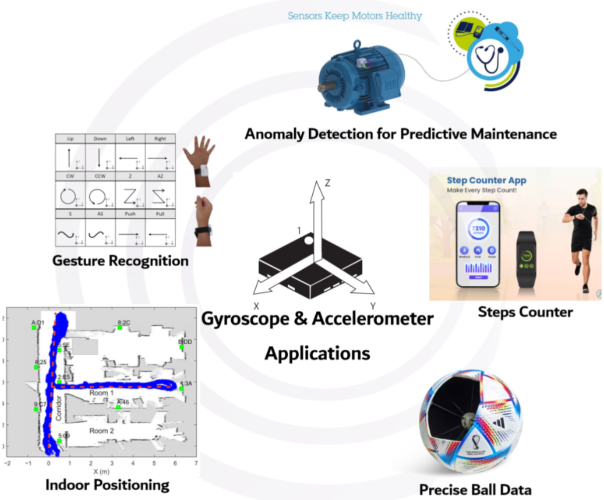


Smartphone orientation



Autonomous vehicles

IMUs and MARG Sensors



Sensor Fusion Concept

- Individual sensors have complementary strengths: - **gyroscopes** measure rotation but drift over time, **accelerometers** measure tilt via gravity but are noisy during movement, **magnetometers** give heading but are disturbed by local fields.
- Sensor fusion algorithms (e.g., Kalman[15][7][16] or complementary filters[11]) combine these readings to obtain a stable orientation estimate. By using multiple sensors, we can "reduce orientation drift introduced through the gyroscope measurements" using gravity and magnetic references.

Goal

The goal is to filter out noise and biases: high-frequency noise from accelerometers is smoothed, while low-frequency gyro drift is corrected by accelerometer/magnetometer data, yielding a robust attitude estimate.

Complementary Filter (CF) Approach

- The complementary filter **fuses gyro and accelerometer data** by applying a high-pass filter to the **gyro** (tracking quick changes) and a low-pass filter to the **accelerometer** (tracking slow changes)[11].

General Equation of the weighted sum

$$\theta(t) = (1-\alpha)\,(\textbf{gyro-integrated angle}) + \alpha\,(\textbf{accel-derived angle})$$

- The blending weight α (between 0 and 1) is tuned based on sensor characteristics.
- This yields the **"best of both worlds"**: the gyro provides a smooth angle during motion, and the accelerometer corrects long-term drift. Properly tuned, the CF can yield orientation with low noise and low.

Complementary Filter: Pros and Cons

Advantages

- Very simple and efficient to implement on micro-controllers.
- Requires minimal computation.
- Effectively reduces random noise (accelerometer) and drift (gyroscope)[18].

Disadvantages

- Fixed filter gains cannot adapt to changing dynamics or sensor conditions.
- Gyroscope biases over time introduce drift if not perfectly zeroed.
- Assumes a stable magnetic reference—magnetic disturbances cause yaw drift.

In summary, CF is computationally light and effective for many scenarios but can struggle during aggressive motion or magnetic interference, motivating adaptive extensions.

Uses and Applications

Consequences of Poor Orientation Estimation

- In **VR/AR**, **incorrect orientation** causes virtual objects to **lag or shift unexpectedly**, leading to user disorientation or motion sickness. The "reality" no longer matches the user's motions.
- In **navigation (drones, aircraft, robotics)**, **bad attitude estimates** can cause control errors or crashes. For example, a drone in strong magnetic interference may misread its yaw and slowly rotate off course.
- **Inertial systems** are immune to jamming (no external signals needed), but they rely on **sensor accuracy**. If magnetic disturbances occur, a MARG system "will over time result in a drift in the heading estimate".

Therefore, improving orientation accuracy is critical for safety and user experience.

Data-Driven and Machine Learning Methods

- Modern approaches use **data analysis and machine learning** to enhance orientation filters. For example, auxiliary sensor data (like eye tracking) can be fused to detect motion phases and correct drift.
- Machine learning can learn **complex biases or map raw sensor patterns to orientation**, effectively "calibrating" IMUs from data. Recent studies show ML-tuned filters outperform fixed filters in sports and motion tracking.
- This aligns with the data science paradigm: extracting knowledge and patterns from data to make better. By analyzing large IMU datasets, ML models can improve orientation estimates beyond classic CF assumptions.

Best of both worlds?

Combining **traditional filters** with **data-driven tuning** offers more adaptive, accurate orientation estimation [19].

Literature Review

Literature Review (Paper 1)

Adaptive Attitude Estimation Using a Hybrid Model-Learning Approach (2022) [19]

Authors: Eran Vertzberger, Itzik Klein

Journal: IEEE Transactions on Instrumentation and Measurement

Overview:

Demonstrates a **hybrid adaptive complementary filter** that learns axis-specific accelerometer weights via neural networks. Quaternion gyro data is integrated and a complementary update is applied in each axis whose weight is predicted by a small neural network based on estimated linear accelerations.

Evaluation:

- Smartphone IMU dataset (60 two-minute sequences of walking activities in pocket, hand, etc., with VI-SLAM ground truth)

Benchmark:

- Fixed-gain filters (Mahony[14], Madgwick[13])

Contributions:

- Learned filter (DAE) yielded the lowest roll/pitch errors (10–37% better than classic filters).
- Adapts to dynamic motion via data-driven weight tuning.
- Outperforms fixed gains under varying conditions.

Disadvantages:

- Requires labeled training data and offline learning.
- Neural nets add complexity.
- Yaw is not addressed (no magnetometer fusion).

Literature Review (Paper 2)

A Robust Complementary Filter Approach for Attitude Estimation of Unmanned Aerial Vehicles using AHRS (2019) [1]

Authors: Johann Meyer, Kreelan Padayachee, Benjamin A. Broughton

Conference: CEAS EuroGNC 2019

Overview:
Explicitly detects when accelerometers are unreliable based on "steadiness" measure (using a low-pass on the accel magnitude) to decide if the vehicle is in steady flight. When unsteady, the filter relies on gyro propagation only; when steady, normal fusion occurs. A Gaussian random-walk model for gyro bias is implemented that rejectsimprobable bias drifts during maneuvers. **Evaluation:**

- Monte Carlo simulations (maneuvering UAV trajectories)

Contributions:

- Monte Carlo simulations show their filter tracks roll dynamics more accurately than standard CFs[11].
- Simple gating logic avoids gross errors from accelerometer disturbances.
- Robust gyro bias handling.

Disadvantages:

- Effectively disables accelerometer fusion during dynamics (so short-term drift may grow).
- Requires tuning of "steadiness" thresholds.
- Only tested in simulations.

Literature Review (Paper 3)

Adaptive Complementary Filtering Algorithm for IMU Based on MEMS (2020) [21]

Authors: Zhang Zhe, Wang Jian-bin, Song Bo, Tong Guo-feng

Conference: 2020 Chinese Control and Decision Conference, CCDC, IEEE

Overview:

An **adaptive sparse-interpolation CF (ASICF)** has been proposed for MEMS IMUs. A quaternion-based complementary filter is used to fuse gyro and accel, but an adaptive data-skip mechanism is added: the filter monitors consecutive accelerometer samples, assesses the "trustworthiness" of the accel (via its variation), and if the data are too noisy or dynamic, it performs an interpolation step rather than using the raw sample (downsampling).

Evaluation:

- Multiple datasets (drone, car, human motion)

Benchmark:

- Fixed-gain filters (Mahony[14], Madgwick[13]),

Contributions:

- Reported significantly lower attitude errors under large disturbances (e.g. 20% smaller error than the Valenti CF [18]).
- Can handle sudden motions by effectively smoothing or skipping bad accelerometer readings.
- Retains quaternion CF structure.

Disadvantages:

- Performance depends on correctly detecting outliers.
- May introduce lagging when interpolating

Literature Review (Paper 4)

A Variable Gain Complementary Filtering Fusion Algorithm Based on Distributed Inertial Network and Flush Air Data Sensing (2023) [17]

Authors: Weiguang Shao, Jianwen Zang, Jin Zhao and Kai Liu

Journal: Applied Sciences (ISSN 2076-3417) 2023, MDPI

Overview:
A **variable-gain CF for aircraft angle-of-attack estimation** is introduced which uses a distributed IMU network plus flush-air sensors. A flight-phase-dependent blending factor is derived: the filter coefficient (analogous to α) which is allowed to vary with the change rate of the angle-of-attack, placing more weight on inertial data at high dynamics.

Contributions:

- Simulation results for a high-speed UAV show this VGCF yields significantly smaller AoA error than a constant-gain INS+FADS filter (approximately 0.0058° vs 0.0017° RMSE, i.e. $>2\times$ improvement)
- Adapts filtering to flight conditions, mitigating delay in air-data measurements

Disadvantages:

- Heavily domain-specific (flush-air data, aerodynamic model).
- Complexity of inertial network fusion.

Literature Review (Paper 5)

Denoising IMU Gyroscopes With Deep Learning for Open-Loop Attitude Estimation (2020) [4]

Authors: Martin Brossard, Silvère Bonnabel, Axel Barrau

Journal: IEEE Robotics and Automation Letters (Volume: 5, Issue: 3, July 2020)

Overview:
A **deep convolutional network** to denoise IMU gyroscopes for open-loop attitude estimation is introduced, where a CNN (with dilated convolutions) is trained on ground-truth data so that it outputs corrected gyro increments. The orientation is then obtained by simply integrating these denoised increments in dead-reckoning. Their loss is carefully designed for angular increments, and no RNNs are used (making inference fast).

Evaluation:

- EuRoC and TUM-VI Datasets

Contributions:

- Outperforms state-of-the-art methods and even beats top visual–inertial odometry algorithms in attitude accuracy.
- End-to-end learned correction captures complex noise/scale drift.
- No vision needed yet achieves very low drift.

Disadvantages:

- Requires large ground-truth datasets for training design is more complex.
- Open-loop mode still drifts (albeit slower).
- Network complexity.

Literature Review (Paper 6)

Generalizable End-to-End Deep Learning Frameworks for Real-Time Attitude Estimation Using 6DoF Inertial Measurement Units (2023) [2]
Authors: Arman Asgharpoor Golroudbari, Mohammad Hossein Sabour
Journal: Measurements (Volume 217, 113105) Elsevier

Overview:
An **end-to-end neural IMU attitude estimator** is proposed. Two deep models (CNN+BiLSTM+FC) are trained to directly map 6-DOF IMU sequences to quaternions. Training uses seven public datasets (120+ hours of motion). Their models generalize across different motions, sampling rates and disturbances, and they report higher accuracy than prior methods.

Evaluation:

- Seven public datasets including EuRoC and TUM-VI

Contributions:

- Leverages temporal convolution and recurrent units for rich modeling.
- Tested on massive diverse data

Disadvantages:

- Heavy models requiring long training.
- **"Black box"**, so no physical insight.
- Relies on availability of similar data during training.

Gaps and Opportunities (1/3)

Lack of Real-Time Adaptivity

- Static parameters cannot adapt to dynamic changes [13][11][9]
- Unexpected accelerations degrade accuracy [10]

Solution: Adaptive Learning

- Dual-XGBoost adjusts fusion weights online from incoming IMU data.
- Responds dynamically to abrupt motions or disturbances.

Lack of Explicit Noise Prediction

- Assumes constant noise [15][16][7] can't predict sensor drift [8].
- Can't handle temperature-induced or vibration noise changes[8].

Solution: Predictive Noise Modeling

- XGBoost predicts gyro bias/variance from real-time sensor data.
- Learns time-varying noise models to maintain estimation accuracy.

Gaps and Opportunities (2/3)

Over-Reliance on Fixed Gains

- Fixed gains cause large estimation errors in dynamic motions [10][13]
- Can't balance between under-correction and over-correction[17][15]

Solution: Dynamic Gain Tuning

- XGBoost adaptively infers fusion weights from current IMU readings.
- Eliminates need for manual gain tuning.

Challenge: Heavy Computational Burden

- DNNs[2][1][4] and advanced EKFs[15][7] are too heavy for real-time embedded systems.
- Require GPUs or powerful processors[6].

Solution: Lightweight Inference

- XGBoost is efficient at runtime: fast tree traversal, no heavy matrix ops.
- Suitable for real-time operation on micro-controllers.

Gaps and Opportunities (3/3)

Loss of Interpretability

- Deep models[2][1][4] are black-box; internal logic is opaque.
- Lack of physical insight makes debugging difficult [6].

Solution: Transparent Design

- XGBoost trees are interpretable: splits and feature importance visible.
- Fusion logic explicitly maintains ties to physics.

Proposed Solution

Proposed Modified Complementary Filter

Noise Prediction & Removal [4]

- Input raw sensor (acc, mag, gyro) columns: $a_i = (a_{ix}, a_{iy}, a_{iz})$, $m_i = (m_{ix}, m_{iy}, m_{iz})$, $g_i = (g_{ix}, g_{iy}, g_{iz})$.
- Trained regressor predicts noise components η_a, η_m.
- Denoised vectors:

$$a_i = a_i - \eta_a, \quad m_i = m_i - \eta_m$$

$$a_{\mathsf{pred}} = R_g * a_{(i-1)pred}(1 - \alpha) + \alpha * a_i$$

$$m_{\mathsf{pred}} = R_g * m_{(i-1)pred}(1 - \alpha) + \alpha * m_i$$

- In the above equations R_g is the quaternion or rotation matrix [3][5].

Movement Prediction & α Toggling [19]

- Toggling Engine analyzes g_i (gyro) patterns to classify motion state.
- Generates adaptive gain α based on predicted movement (static vs. dynamic).
- Compute gyro-based update:

$$R_g = \exp\Big(\Omega_\times(g_i)\,\delta t\Big)$$

  where $\Omega_\times$ is the skew-symmetric operator [20].
- Final CF fusion in 24:

$$R = (1 - \alpha)\,R_g \; + \; \alpha\,R_{am}.$$

Proposed Modified Complementary Filter

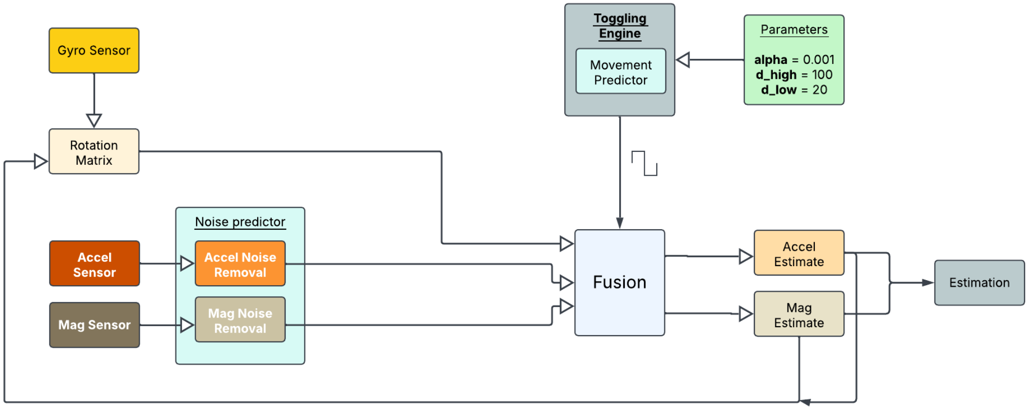


Figure: Toggling Engine: Modified Filter Diagram with Noise Prediction and Movement Prediction

XGBoost Ensemble

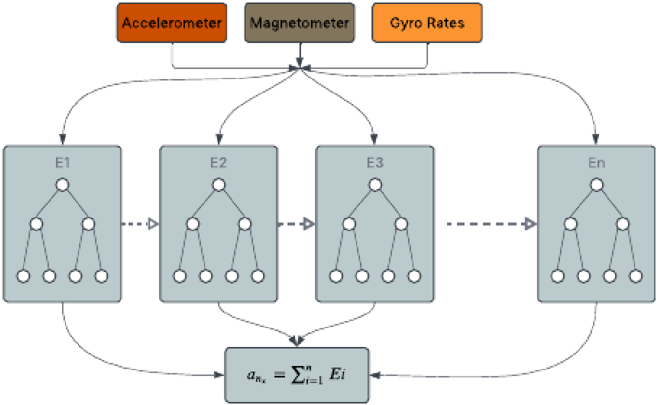


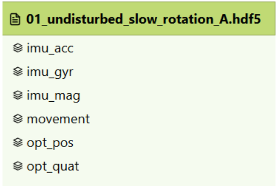
Figure: Prediction of One component of noise through an Ensemble model(XGB in our case)

Dataset Overview: BROAD

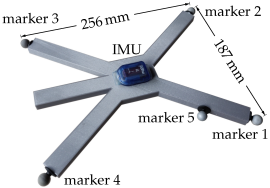
- **Berlin Robust Orientation Estimation Assessment Dataset (BROAD)** [12]
- **Trials:** 39 recordings of predefined motions
- **Sampling:**
  - OptiTrack ground truth: position opt_pos & orientation opt_quat at 120Hz
  - IMU MARG data: accelerometer, gyroscope, magnetometer at 286Hz
  - Boolean movement flag per timestamp
- **Hardware:**
  - Custom 3D-printed mount with myon aktos-t 9-axis IMU
  - Optical markers for tracking by OptiTrack OMC system
- **Motion types:** undisturbed (rotation, translation, combined; slow/fast) and disturbed (tapping, vibration, magnets, office, mixed)
- Detailed protocol in the BROAD paper: `https://www.mdpi.com/2306-5729/6/7/72`

Dataset Details: Categories & Hardware

Motion Type	Speed	Indices
Undisturbed		
Rotation	Slow	01–05
Rotation	Fast	06–09
Translation	Slow	10–14
Translation	Fast	15–18
Combined	Slow	19–20
Combined	Fast	21–23
Disturbed (Medium Speed)		
Tapping	—	24–25
Vibrating Smartphone	—	26–27
Stationary Magnet	—	28–31
Attached Magnet (1–5)	—	32–36
Office Environment	—	37–38
Mixed	—	39



(a) Dataset columns overview



(b) 3D-printed mount with IMU (OptiTrack markers)

Experimental Setup

Training to Predict Movement: Dataset

- **Movement Prediction Model:** Train **XGB classifier** to predict if the IMU is in motion.
- **Noise Prediction Model:** Train **XGB regressor** to predict noises in raw accelerometer data.
- **Implementation of the Modified CF:** Implementation of our proposed algorithm in python and evaluating it through the BROAD dataset trials.

Results

Results of α-toggling with and without denoising across cross-validation files in BROAD

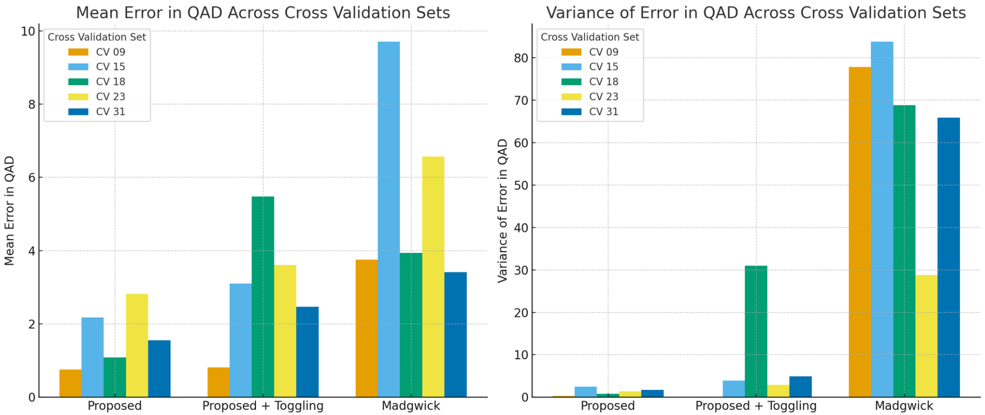


Figure: Mean error statistics (with and with denonising) across cross-validation files in BROAD

Static Error Metrics with and without ML Denoising

Table: Static error metrics (°).

Metric	Prop. (ML)	Prop. (no ML)	Madg.	Aqua	EKF
mean	23.1	14.99	79.71	***10.64***	39.05
std	2.24	***1.06***	8.44	2.16	19.18

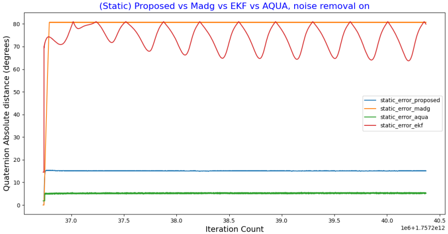


Figure: Static Error with Denoising

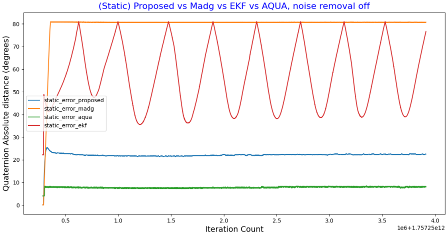


Figure: Static Error without Denoising

Quasi-Static Error Metrics in X-axis

Table: Quasi-Static error metrics (°) in X-axis

Metric	Prop. (ML)	Prop. (no ML)	Madg.	Aqua	EKF
mean	16.25	14.06	13.45	***12.32***	52.278
std	22.04	***21.03***	21.15	23.9	15.32

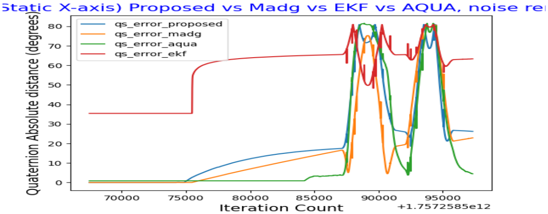


Figure: Quasi-Static Error with Denoising (X-axis)

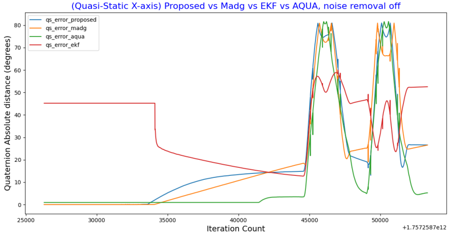


Figure: Quasi-Static Error without Denoising (X-axis)

Quasi-Static Error Metrics in Y-axis

Table: Quasi-Static error metrics (°) in Y-axis

Metric	Prop. (ML)	Prop. (no ML)	Madg.	Aqua	EKF
mean	18.04	17.36	14.77	***11.44***	40.89
std	23.01	24.10	23.89	23.92	***17.5***

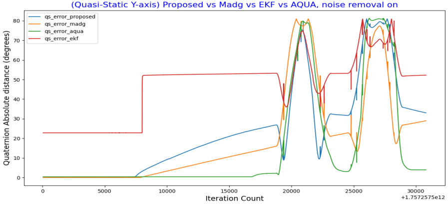


Figure: Quasi-Static Error with Denoising (Y-axis)

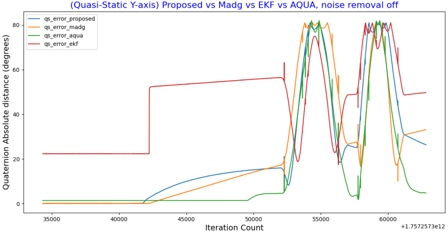


Figure: Quasi-Static Error without Denoising (Y-axis)

Quasi-Static Error Metrics in Z-axis

Table: Quasi-Static error metrics (°) in Z-axis

Metric	Prop. (ML)	Prop. (no ML)	Madg.	Aqua	EKF
mean	9.84	***7.5***	7.98	10.08	32.2
std	10.33	***7.26***	9.77	18.77	18.122

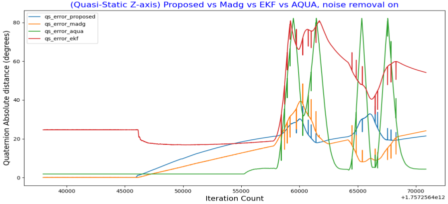


Figure: Quasi-Static Error with Denoising (Z-axis)

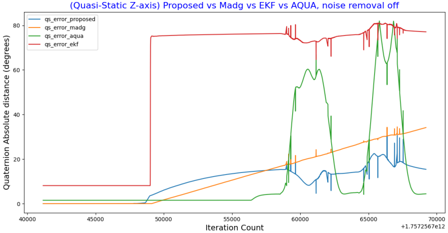


Figure: Quasi-Static Error without Denoising (Z-axis)

Dynamic Error Metrics in X-axis

Table: Dynamic error metrics (°) in X-axis

Metric	Prop. (ML)	Prop. (no ML)	Madg.	Aqua	EKF
mean	30.87	***22.12***	32.35	24.36	47.57
std	31.33	***18.87***	31.86	31.06	19.17

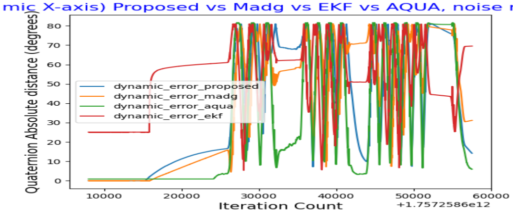


Figure: Dynamic Error with Denoising (X-axis)

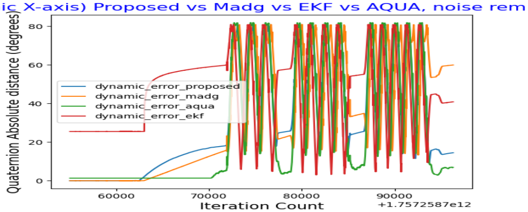


Figure: Dynamic Error without Denoising (X-axis)

Dynamic Error Metrics in Y-axis

Table: Dynamic error metrics (°) in Y-axis

Metric	Prop. (ML)	Prop. (no ML)	Madg.	Aqua	EKF
mean	26.92	33.97	29.90	***22.54***	44.08
std	28.90	29.95	30.74	28.58	***24.48***

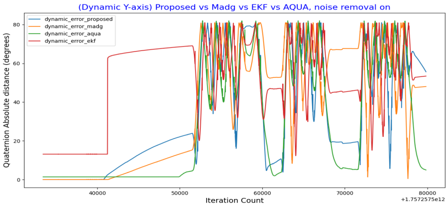


Figure: Dynamic Error with Denoising (Y-axis)

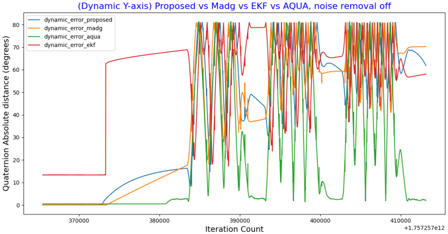


Figure: Dynamic Error without Denoising (Y-axis)

Dynamic Error Metrics in Z-axis

Table: Dynamic error metrics (°) in Z-axis

Metric	Prop. (ML)	Prop. (no ML)	Madg.	Aqua	EKF
mean	29.80	***10.14***	25.41	17.95	30.07
std	28.14	***11.72***	26.86	24.03	17.38

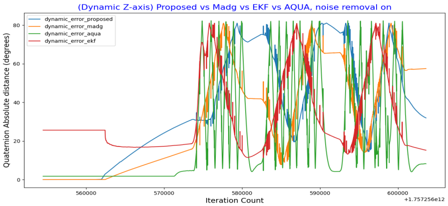


Figure: Dynamic Error with Denoising (Z-axis)

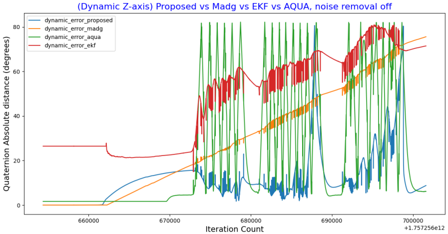


Figure: Dynamic Error without Denoising (Z-axis)

Resource Consumption

Table: Static Error Resource consumption per filter on RPI: average CPU (%) and memory (MB).

Filter	CPU Usage (%)	Memory Usage (MB)
Proposed (ML)	58.6	145.65
Proposed (-ML)	54.5	120.35
Madgwick	***1.75***	59.75
EKF	3.12	59.77
Aqua	2.32	***59.69***

Shortcomings

Shortcomings of Our Data-Driven CF

- **Model Size & Memory:** XGBoost inference is $O(\log n)$ per tree (depth=15, 6 vars, 15 estimators) $\rightarrow$ wide trees consume significant memory.
- **Computational Overhead:**
  - Matrix exponentiation for R_g rotations.
  - RANSAC-based training adds extra latency.
- **Training Time:** RANSAC loop and ensemble fitting are time-intensive.
- **Generalizability:** Noticeable drop in performance on cross-validation vs. test sets.
- **Inconsistency in Axes:** Model seems to perform much better in z-axis but can't keep up the consistency in x and y axes.

Future Works accomplished from pre-defence

Built Single-Axis Turntable with Manual Tilting

- **Low-cost alternative** to 3-axis gimbal for basic yaw control.
- **Controlled Yaw:** Turntable provides precise single-axis rotation.
- **Manual Pitch/Roll:** Tilting mechanism adjusts up–down and side–side angles.
- **Setup Requirements:**
  - Single-axis turntable.
  - Manual tilt mount for pitch roll.
  - Stable platform aligning IMU axes with rotation/tilt axes.
- **Testing Procedure:** Place IMU at center, rotate known angles (e.g. 50° yaw), record gyroscope integration + accel/mag fusion estimates and compare to known rotation [22].

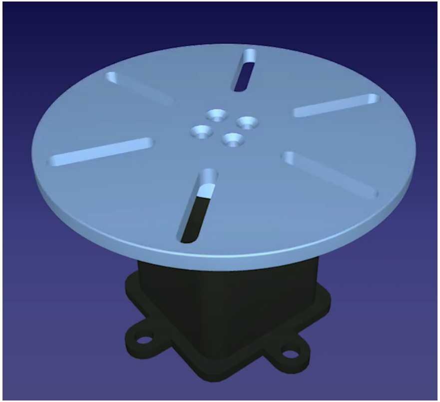


Figure: Single-axis turntable with manual tilt mechanism.

Evaluation Methodology

Data & Protocol

- Single MARG dataset for all tests (accel, gyro, mag).
- Controlled motions via gimbal and turntable setups.
- Identical trajectories, speeds, and motion types.

Algorithms Tested

- Extended Kalman Filter (EKF)
- Madgwick Filter
- AQU Filter
- Proposed Modified Complementary Filter

Comparison Metrics

- **Accuracy:** RMSE of roll, pitch, yaw vs. OptiTrack ground truth.
- **Efficiency:**
  - Execution time per sample.
  - Memory footprint.
- **Robustness:**
  - Static vs. dynamic motions.
  - Undisturbed vs. disturbed conditions.

Goal: Assess whether the proposed filter improves accuracy and/or runtime under varied conditions.

Future Works

Future Works

- **Improving generlizability**
- **Improving the error statistics on x and y axes**
- **Improving computational cost and memory usage**

Deployment Challenges & Strategy

Challenge: Resource Constraints

- XGBoost model size: 25MB flash memory
- ESP32 max flash: 4MB
- Limited CPU and RAM on embedded platforms

Proposed Strategy

- **Model Optimization:**
  - Quantization & pruning
  - Tree depth reduction
  - Converter to light-weight formats (e.g., Treelite)
- **Fallback Deployment:**
  - If ESP32 still infeasible, deploy on Raspberry Pi
  - Leverage its higher memory and CPU capabilities

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Thank you!