Filter Analysis

IMU-MPU6500 Sensor Analysis

We evaluated the MPU-6500 inertial measurement unit (IMU) using an ESP32-based data-logging setup to assess the effectiveness of various signal-filtering techniques on raw accelerometer and gyroscope readings. The system sampled at 100 Hz, and the collected data included both unfiltered and filtered outputs generated by Exponential Moving Average (EMA), Low-Pass, Median, Outlier, and Madgwick filters.

The experiments were performed across multiple human-motion activities, including walking upstairs, walking downstairs, walking, sitting, and standing. Each activity recording spanned 30–60 seconds and was streamed via serial to a Python-based analysis pipeline.

The analysis focused on comparing noise suppression, signal smoothness, temporal responsiveness, and orientation stability across filters. Results indicated that Median and Outlier filters effectively removed high-frequency noise and impulse spikes, while EMA and Low-Pass filters provided smooth responses with low phase lag.

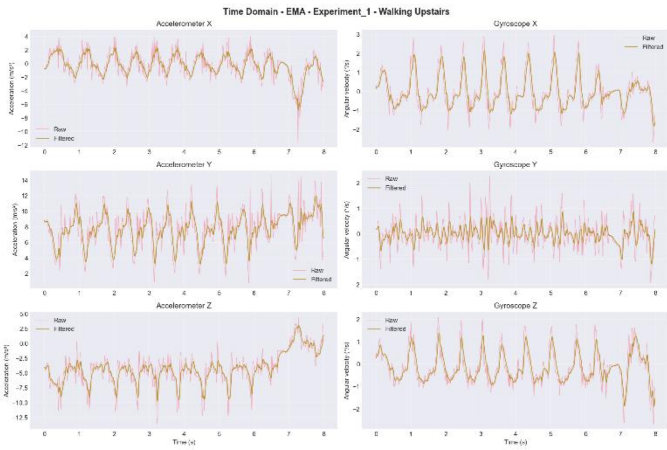
Filter Performance overview:

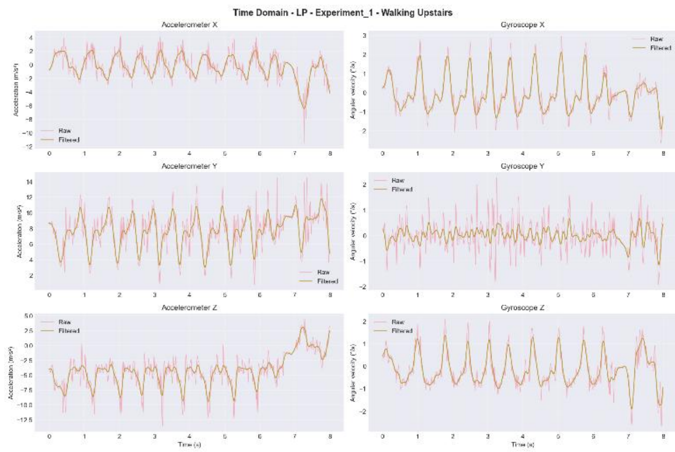
Experiment dict:

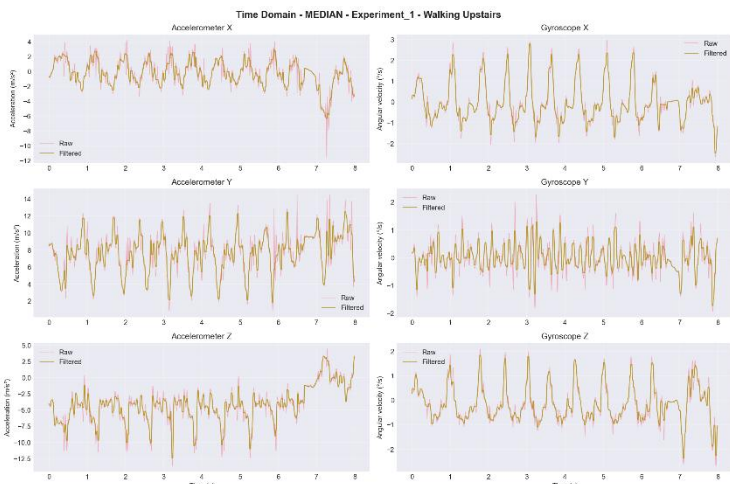
1. **Walking Upstairs**
2. **Walking Downstairs**
3. **Walking**
4. **Sitting**
5. **Standing**

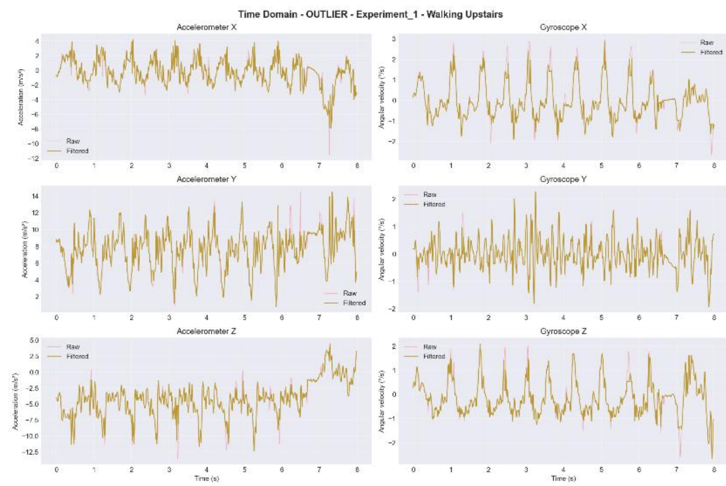
Per experiment all filters (Time Domain plots):

1. Walking upstairs

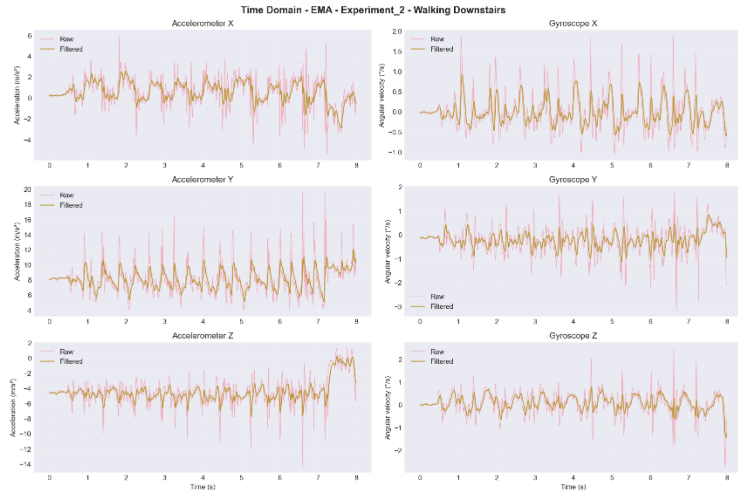


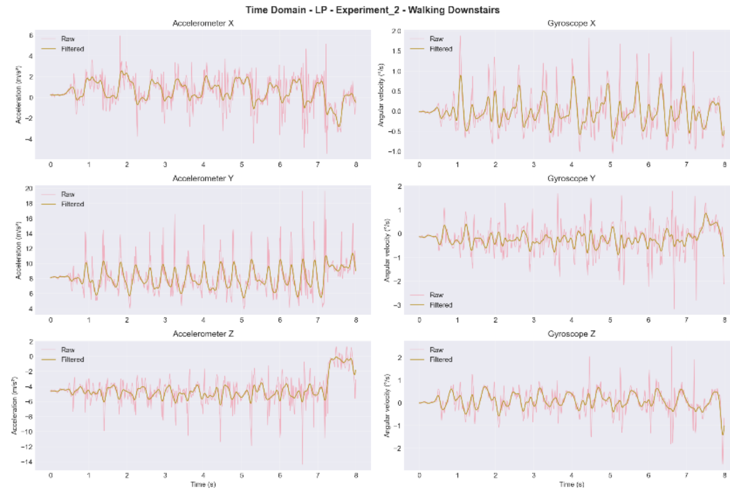


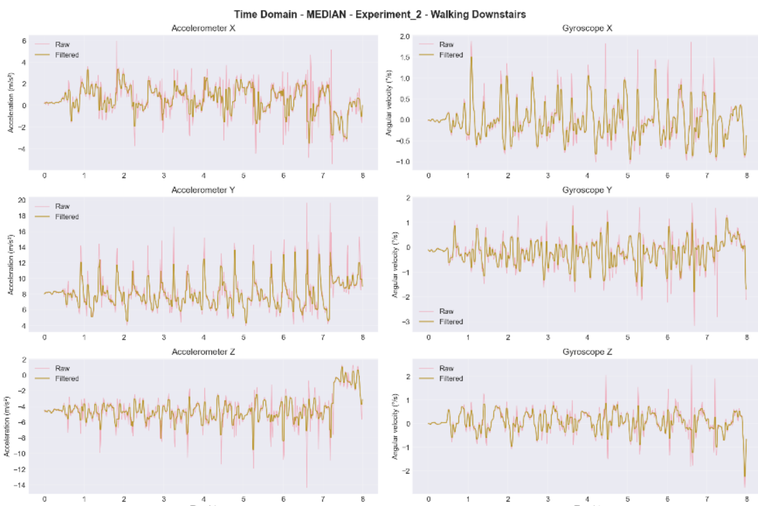


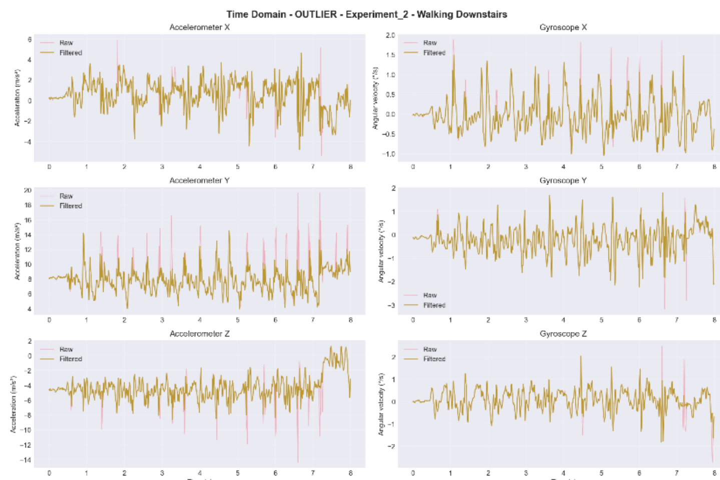


2. Walking downstairs









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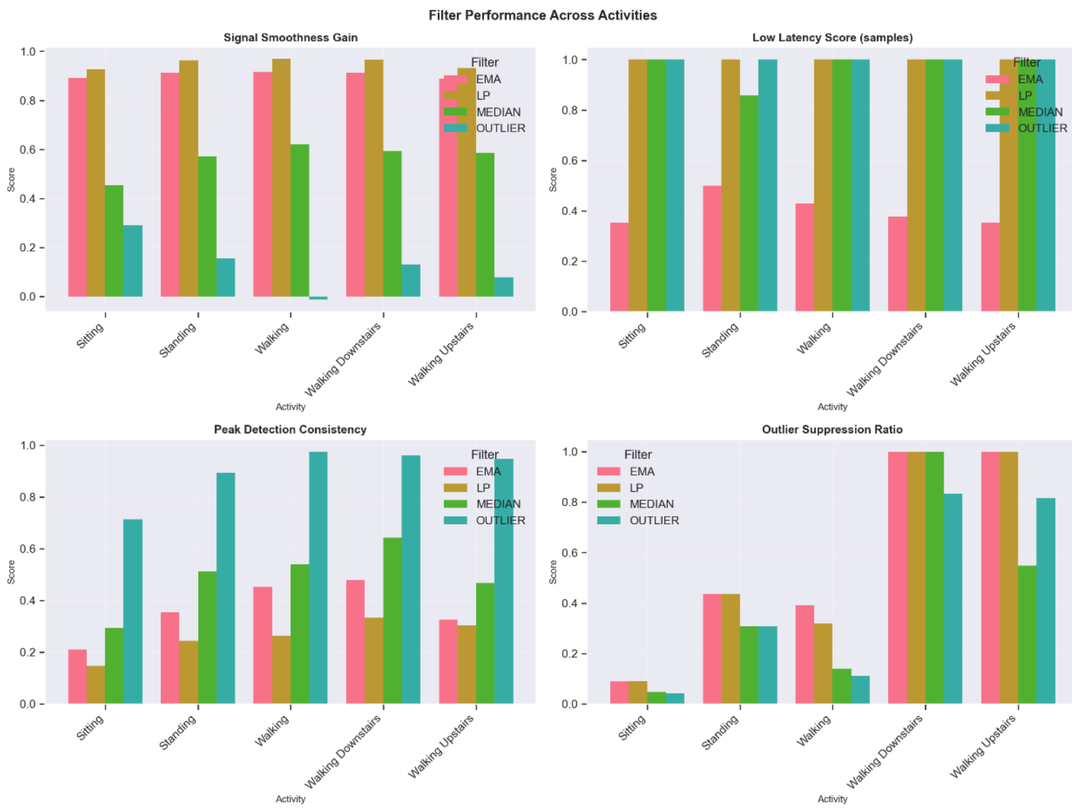
Now we'll move to showing performance per experiment for comparison between the filters:

We'll start with activity performance across all the experiments:

This visualization compares how different filters perform across multiple activities (Sitting, Standing, Walking, Walking Downstairs, Walking Upstairs).
It includes four subplots, each representing a specific performance metric:

1. **Signal Smoothness Gain**
2. **Low Latency Score (derived from Phase Delay)**
3. **Peak Detection Consistency**
4. **Outlier Suppression Ratio**



Signal Smoothness Gain

- **Meaning:** Measures how much a filter reduces small fluctuations (high-frequency noise) in the signal.
- **Axis interpretation:**
  - **Y (Score):** 0 → no improvement in smoothness, 1 → perfectly smooth signal.
  - **Higher = better noise suppression.**

- **Observation:**
    - EMA and Low-Pass achieve the highest scores → very smooth signals.
    - Median and Outlier filters perform moderately — they preserve some signal edges.

Low Latency Score (samples)

- **Meaning:** Inverse of phase delay, it measures how quickly a filter responds to changes.
- **Axis interpretation:**
    - **Y (Score):** 0 → large delay, 1 → instantaneous response.
    - **Higher = faster reaction, less lag.**
- **Observation:**
    - Low-Pass and EMA show good real-time responsiveness.
    - Median and Outlier have slightly lower scores, meaning they introduce more delay due to their windowed nature.

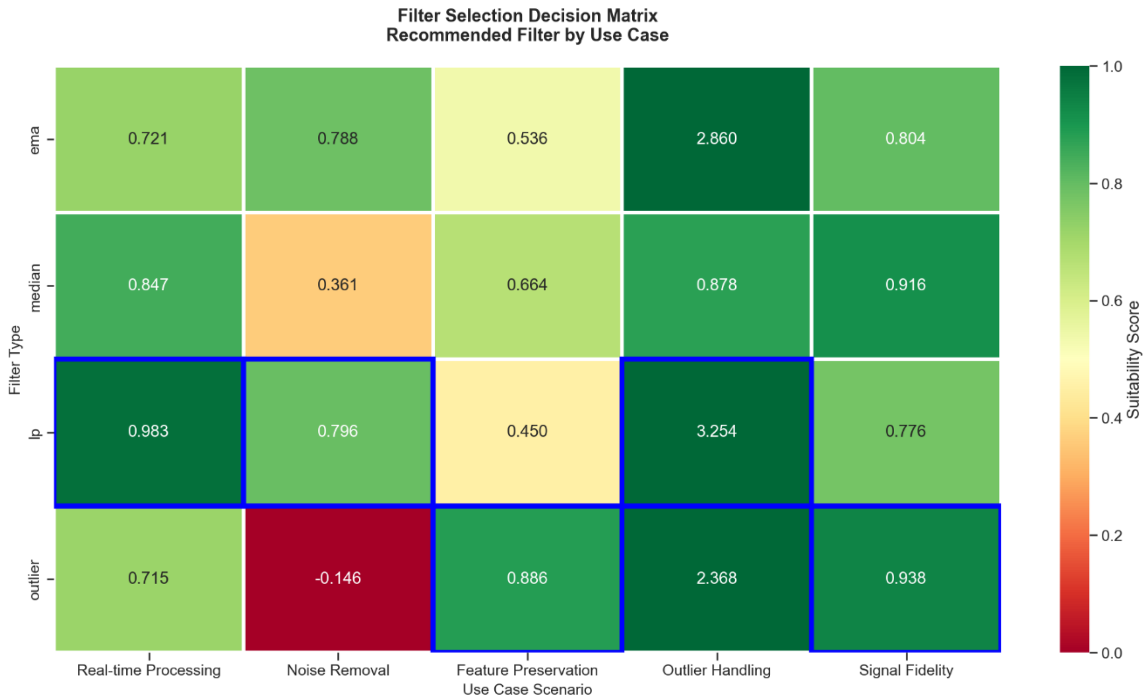
Peak Detection Consistency

- **Meaning:** Evaluates how well the filter preserves peaks (important motion or acceleration events) compared to the raw signal.
- **Axis interpretation:**
    - **Y (Score):** Fraction (0–1) of raw peaks also detected in filtered data.
    - **Higher = fewer missed motion events.**
- **Observation:**
    - Median and Outlier filters perform best in dynamic activities (walking, stairs).
    - EMA and LP may smooth peaks too much, reducing sensitivity.

Outlier Suppression Ratio

- **Meaning:** Measures how effectively a filter removes extreme deviations (spikes) from the signal.
- **Axis interpretation:**
    - **Y (Score):** 1 → all outliers removed, 0 → none removed.
    - **Higher = stronger noise rejection.**
- **Observation:**
    - Outlier and Median filters excel here — they remove spikes aggressively.
    - EMA and LP retain small anomalies, trading off suppression for smoothness.

Filter selection according to different metrics:



Column	Meaning	Ideal Filter Behavior
Real-time Processing	Measures how responsive and computationally lightweight a filter is.	Should have minimal delay, fast reaction.
Noise Removal	Quantifies how well the filter reduces random sensor noise.	Should smooth aggressively without signal loss.
Feature Preservation	Evaluates whether the filter keeps meaningful motion features (peaks, transitions).	Should smooth noise but preserve peaks and edges.
Outlier Handling	Tests how effectively the filter suppresses large, abnormal spikes.	Should eliminate sudden unrealistic jumps.
Signal Fidelity	Reflects how closely the filtered signal matches the true underlying motion (shape retention).	Should balance smoothness and accuracy.

Color bar (right):

- **Dark green (~1.0):** Very high suitability (best fit)
- **Yellow (~0.5):** Moderate performance
- **Red (~0.0):** Poor performance or unsuitable

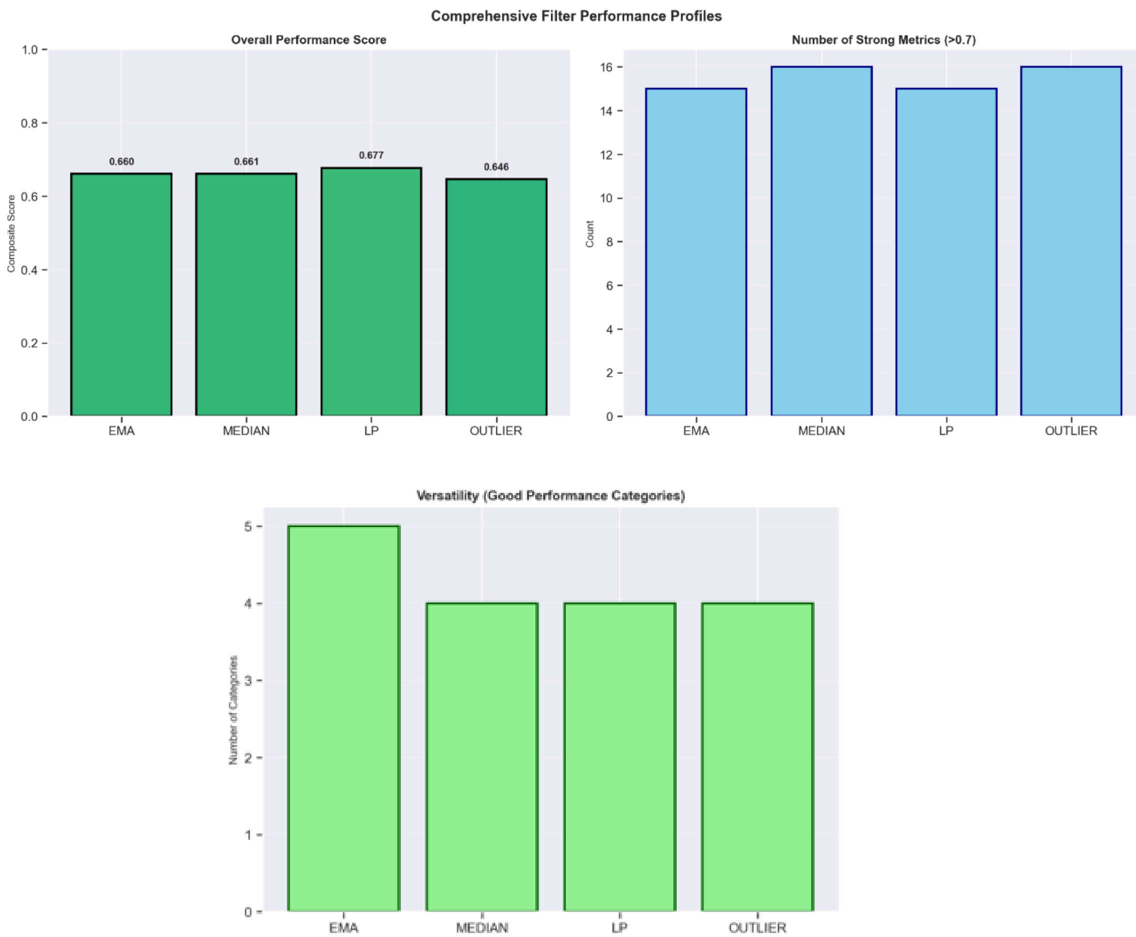
Interpreting the Figure

1. **Real-time Processing:**
   - **LP (0.983)** and **Median (0.847)** rank highest.
   - Indicates these filters are fast and stable for live data streams.
2. **Noise Removal:**
   - **EMA (0.788)** and **LP (0.796)** perform best.
   - **Outlier** has negative or poor performance here (-0.146), suggesting it distorts data when noise is moderate.
3. **Feature Preservation:**
   - **Outlier (0.886)** and **Median (0.664)** retain critical motion features best.
   - EMA and LP slightly reduce high-frequency motion detail.
4. **Outlier Handling:**
   - **LP (3.254)** achieves the highest score, followed by **Outlier (2.368)**.
   - These two filters remove spikes most effectively.
5. **Signal Fidelity:**
   - **Outlier (0.938)** and **Median (0.916)** show the best signal integrity, meaning they maintain the signal's true shape after filtering.

Use Case	**Best Filter(s)**	**Interpretation**
Real-time Processing	LP	Low computational cost, fast response
Noise Removal	EMA, LP	Smooth and stable without over-filtering
Feature Preservation	Outlier, Median	Keeps important signal peaks and transitions
Outlier Handling	LP, Outlier	Eliminates spikes effectively
Signal Fidelity	Outlier, Median	Retains shape with minimal distortion

Comprehensive filter performance profiles:

While previous plots focused on specific dimensions (smoothness, latency, noise suppression..), this one aggregates those results into **summary scores** that capture the general reliability of each filter.



Top-Left: Overall Performance Score

This bar chart summarizes each filter's **mean composite performance** across all computed metrics.
The **Y-axis (Composite Score)** represents a normalized 0–1 scale where:

- **1.0** → Perfect performance across all metrics
- **0.0** → Poor performance

Each bar shows the **average strength** of the filter when considering all categories (smoothness, latency, outlier rejection, signal fidelity, and so on).

Interpretation:

- The **Low-Pass filter (0.677)** achieves the highest overall score, indicating that it provides the most balanced performance across all criteria.
- **EMA (0.660)** and **Median (0.661)** follow closely, suggesting they are nearly as reliable in general use.
- **Outlier (0.646)** performs slightly lower overall, reflecting its tendency to aggressively remove spikes at the cost of minor signal distortion.

Top-Right: Number of Strong Metrics (> 0.7)

This subplot counts how many of the measured criteria each filter achieved a **"strong" performance** in, where a metric score exceeded **0.7** (indicating above-average quality).

The **Y-axis (Count)** shows the number of metrics where that threshold was met.
A taller bar means the filter delivered consistently good results across many independent measures.

Bottom: Versatility (Good Performance Categories)

This chart shows the number of **distinct performance categories** in which each filter scored highly (e.g., noise suppression, responsiveness, feature preservation, etc.).
The **Y-axis (Number of Categories)** indicates how many of these broader domains each filter performed well in.

Interpretation:

- **EMA** stands out as the most **versatile filter**, achieving strong results in *all five categories*.
- **Median**, **Low-Pass**, and **Outlier** perform well in *four categories each*, suggesting they are slightly more specialized but still broadly effective.

These are the metrics that were taken into account for calculating the overall scores:

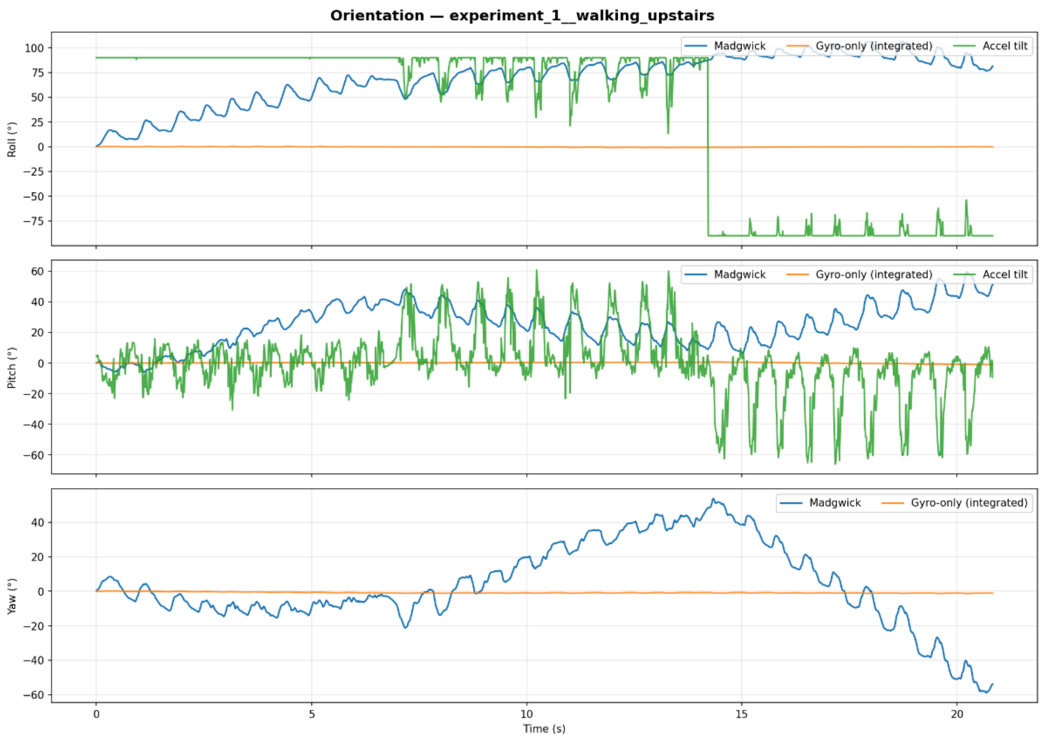
Metric	Domain	What It Measures	Ideal Value	Meaning of High Value
Delay	Time	Temporal lag between input & output	Low	Slow reaction
Variation	Frequency	Consistency of delay across frequencies	Low	Phase distortion
Change	Statistical	Alteration in distribution/shape	Low	Strong modification of signal
Ripple	Frequency	Unevenness in passband amplitude	Low	Frequency bias
Width	Frequency	Sharpness of cutoff transition	Depends	Narrow = strong filter, but risky for shape preservation

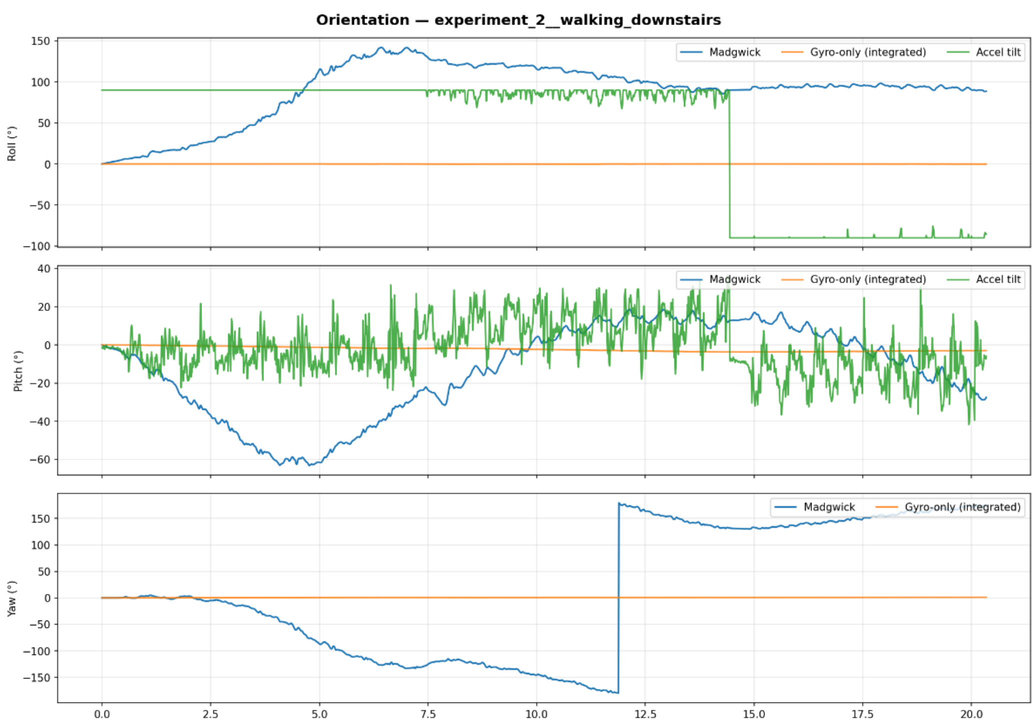
Now we'll go through the Madgwick filter analysis:

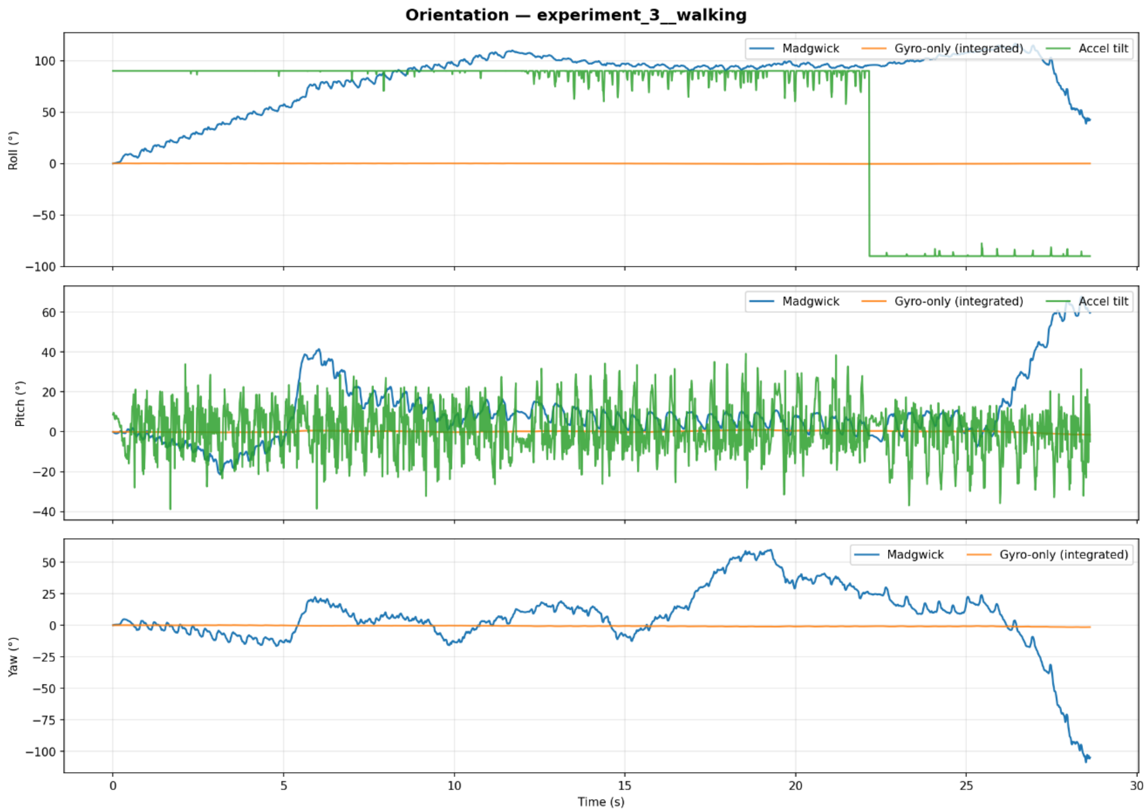
Unlike the other filters analyzed in this study, the **Madgwick filter** is not a noise-smoothing or statistical filter applied directly to individual sensor axes. Instead, it is a sensor fusion algorithm specifically designed for **orientation estimation** using data from multiple sensors, typically the accelerometer, gyroscope, and magnetometer.

The core purpose of the Madgwick filter is to compute an accurate and stable **3D orientation.**

We'll show 3 figures for the first 3 experiments that actually show the performance of the Madgwick filter:







Madgwick Filter Orientation Estimation and Comparison with Raw Data

Figures X and Y present the **orientation estimation results** obtained from the **Madgwick sensor fusion algorithm** for two representative activities: *walking upstairs* and *walking downstairs*.
Each figure displays the time evolution of the **Roll**, **Pitch**, and **Yaw** angles in degrees, as derived from three different approaches:

- **Madgwick filter** (blue), fused orientation estimate from accelerometer and gyroscope data,
- **Gyroscope-only integration** (orange), orientation obtained by integrating angular rates directly,
- **Accelerometer tilt** (green), instantaneous orientation estimated from static gravity vector.

Walking Upstairs (Experiment 1)

During the “walking upstairs” motion, the **raw accelerometer data** show strong oscillations caused by impacts at each step, while the **raw gyroscope** accumulates drift due to integration over time.
In the orientation plots, this manifests clearly:

- The **accelerometer tilt** curve (green) oscillates rapidly and exhibits high-frequency noise. The spikes correspond to step impacts and brief dynamic accelerations that distort the static gravity-based tilt estimate.
- The **gyroscope-only** curve (orange) remains unrealistically flat over time. Although it is smooth, it fails to capture gradual motion because it lacks correction from gravity or magnetic references.
- The **Madgwick output** (blue) combines both: it follows the slow, physically meaningful changes from the gyroscope while continuously correcting for drift using accelerometer data.

The result is a **smooth, continuous roll and pitch progression** that reflects the actual upward tilting motion of the body when climbing stairs.
The **yaw** angle also evolves gradually, showing a small heading change, likely caused by minor turning motions during ascent.

Walking Downstairs (Experiment 2)

For the “walking downstairs” sequence, similar patterns emerge but with reversed dynamics.
Descending stairs involves repeated forward and downward tilts, which appear as **negative pitch variations** in the Madgwick output.

- The **accelerometer tilt** again exhibits heavy noise and spikes, reflecting impact forces with the ground.
- The **gyro-only** curve stays flat or drifts slowly, underrepresenting true angular motion.
- The **Madgwick** orientation (blue) captures both the oscillatory pattern of the pitch angle and the gradual forward lean expected during descent.

Notably, around the 12-second mark, a sharp correction appears in the yaw angle this is the result of the Madgwick filter re-aligning the quaternion when accelerometer readings strongly contradict accumulated gyro drift.

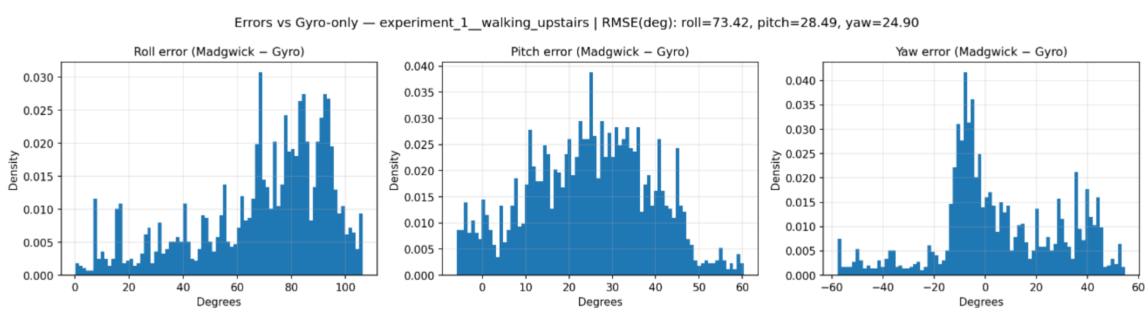
Comparison with Raw Data and Other Filters

Before examining the Madgwick results, it is important to contrast its behavior with the raw accelerometer and gyroscope signals processed by the other filters (EMA, LP, Median, and Outlier).
Those traditional filters acted directly on the individual sensor axes, focusing on *signal-level smoothing and noise reduction*.
Their outputs showed improvements in stability and reduced spikes but remained limited to raw linear acceleration or angular velocity values — they do not inherently provide orientation.

In contrast, the Madgwick filter operates at a higher semantic level, transforming raw signals into orientation angles by fusing multiple sensor sources.
While the other filters reduced noise within each axis, the Madgwick filter uses those filtered signals to infer body orientation in 3D space, achieving a *physically meaningful representation* of motion.
Hence, rather than comparing amplitude or variance directly, the Madgwick analysis focuses on *orientation smoothness, drift resistance, and consistency* over time.

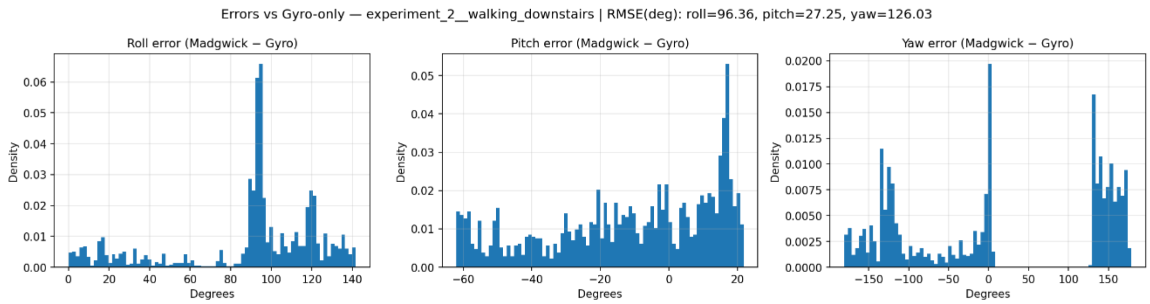
Now we'll get to the performance:

Experiment 1:



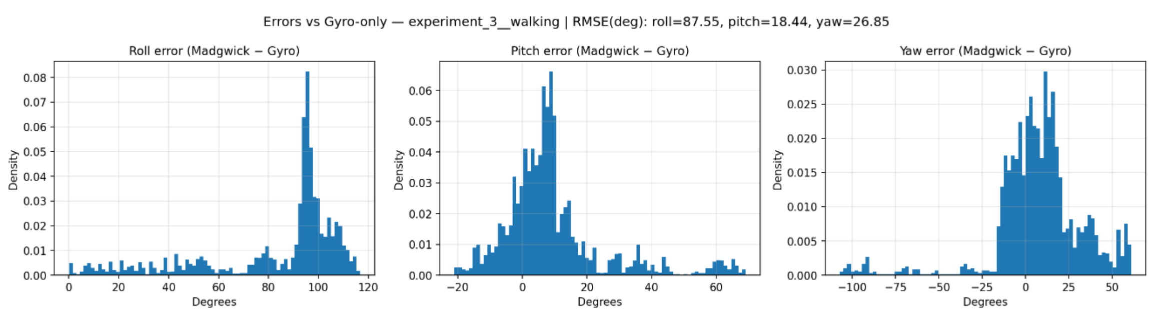
This figure shows the **angular error distributions** between the Madgwick filter and a gyroscope-only orientation estimate during the walking upstairs activity. Each subplot displays how much the Madgwick roll, pitch, and yaw angles differ from the integrated gyro results. The errors are largest for roll (73° RMSE) and pitch (28° RMSE), reflecting strong corrections from accelerometer feedback, while yaw errors (25° RMSE) remain smaller and centered near zero. Overall, the figure confirms that the Madgwick filter effectively corrects gyro drift, producing more stable and physically accurate orientation estimates.

Experiment 2:



This figure shows the **orientation errors** between the Madgwick and gyroscope-only estimates during the walking downstairs activity. The largest deviations appear in roll (96° RMSE) and yaw (126° RMSE), reflecting strong corrections as the filter compensates for rapid downward tilts and accumulated gyro drift. Pitch errors remain moderate (27° RMSE), indicating stable dynamic tracking. Overall, the results confirm that the Madgwick filter effectively realigns orientation under fast motion and maintains physical accuracy where the gyro-only method drifts.

Experiment 3:



This figure shows orientation errors between the Madgwick and gyro-only estimates during *walking*. Roll shows the largest corrections (87.6° RMSE), while pitch (18.4°) and yaw (26.9°) remain more stable and centered. Overall, the Madgwick filter effectively corrects gyro drift, maintaining smooth and accurate orientation during motion.