Single Pendulum Digital Twin

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Github repo

Introduction

we focused on building a digital representation of a single pendulum mounted on a movable cart. Our goal was to annotate and process real-world sensor data to model the system's behavior accurately. The work started with designing and collecting datasets under different scenarios, including cart movements, pendulum swings, and angle extremes.

To make the encoder readings meaningful, we ran a series of controlled cart movements with known distances and durations. We mapped these movements to encoder tick differences and calculated both cm/tick and ticks/cm ratios. The results showed consistent values across various movement distances, confirming reliable encoder calibration.

We then applied a Kalman filter to reduce noise in the accelerometer and encoder data. FFT-based filtering was also used to isolate dominant frequencies and remove high-frequency noise. For angle estimation, we explored filtering techniques and validated them by comparing with known motion patterns.

Finally, we used grid search and genetic algorithms to optimize parameters such as filter coefficients and thresholds. These methods helped fine-tune the system for better accuracy and responsiveness in the digital twin.

Data Annotation

To better understand and model the behavior of the single pendulum system, we categorized the data into three distinct scenarios based on different types of motion and their corresponding measurements.

Each dataset captures specific dynamics of the system:

1. Cart Movements Dataset (cart_movements_datasets) This dataset focuses on the translational movement of the cart along the track. To generate this dataset, we ran both single cart movements and sequences of movements. The goal was to capture how the cart's displacement affects the overall pendulum behavior.

Example video

2. Pendulum Extremes Dataset (maximums) This dataset aims to record the pendulum's angular limits during its oscillation. Specifically, we attempted to capture the maximum and minimum values of the pendulum angle (θ) as it swings up and down.

These extremes are useful for understanding the physical constraints and natural range of motion of the pendulum.

3. Single Pendulum Movements Dataset (single_pendulum_movements) This dataset isolates the motion of the pendulum itself without active cart movement. The data collected here focuses on the pendulum's oscillatory behavior, enabling us to study its natural dynamics and resonance patterns.

Example video 1

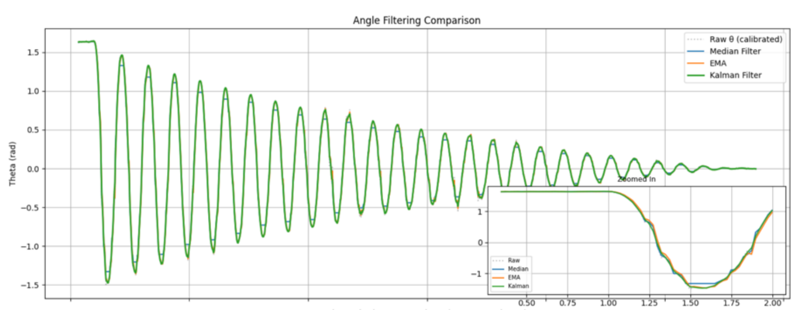
Example video 2

Data Processing, Filtering, and Analysis

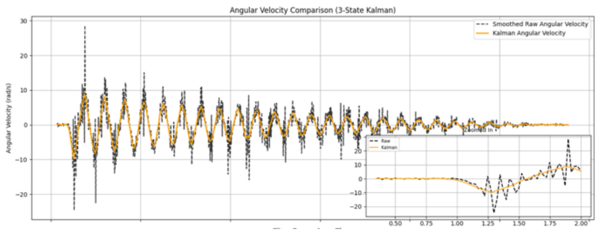
After collecting and organizing the datasets, we focused on processing the single_pendulum_movements dataset to study the natural oscillations of the pendulum without interference from the cart. Our goal was to clean and structure the raw accelerometer and encoder data, then apply signal processing and filtering techniques to estimate the angular position (θ), angular velocity ($\dot{\theta}$), and even angular acceleration ($\ddot{\theta}$) with high accuracy.

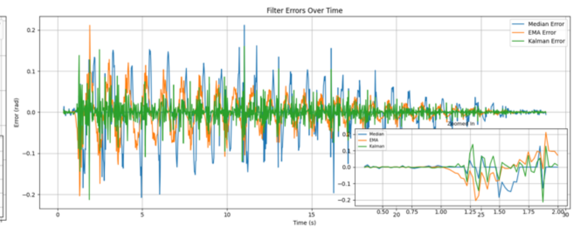
We began by calculating θ using the arctangent of horizontal and vertical accelerometer components and then calibrated it using resting-state measurements to remove any initial bias. Next, we implemented three different filters to denoise the signal: a Median Filter, an Exponential Moving Average (EMA), and a 3-state Kalman Filter that considers θ, $\dot{\theta}$, and $\ddot{\theta}$. The Kalman filter was specifically designed to reflect the physical dynamics of a second-order pendulum system, offering a more realistic estimate of motion.

To evaluate the performance of each filter, we plotted the filtered signals alongside the raw data and zoomed in on a portion of the plot (first 2 seconds) to visualize transient behavior more clearly. The plots showed that while the Median and EMA filters reduced noise to some extent, the Kalman filter not only preserved the shape and phase of the signal better but also provided smoother and more consistent velocity estimates.

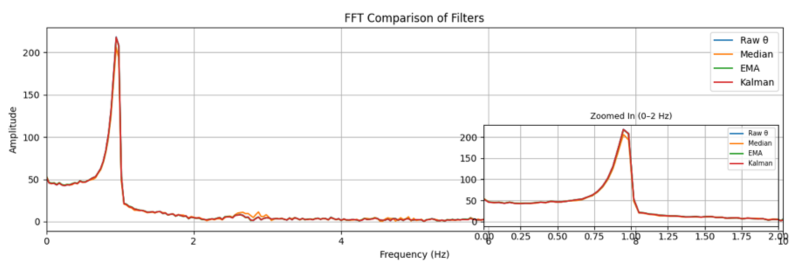


We also compared angular velocity outputs derived from raw data and the Kalman model. It was evident that raw velocity exhibited sharp spikes and fluctuations due to noise, whereas the Kalman estimate was stable and followed the actual pendulum dynamics more accurately. Additionally, we analyzed the residual errors between the raw and filtered signals. Kalman consistently produced the smallest error margins over time.





In the frequency domain, FFT plots confirmed that all filters suppressed high-frequency noise, but the Kalman filter preserved low-frequency components — representing true oscillatory behavior — with minimal distortion. A zoomed-in version of the FFT plot (0–2 Hz) made it even clearer that Kalman filtering maintained the fundamental oscillation frequency, while reducing spectral leakage.



To quantify filter performance, we calculated MSE, MAE, R^2, and SNR for all three filters. The results were visualized using bar charts. Kalman outperformed others in every metric, showing the lowest error values and the highest signal-to-noise ratio and R^2 score, confirming both its precision and reliability.

filters	MSE	MAE	R^2	SNR
Median	0.002079	0.023042	0.993817	22.09 dB
EMA	0.001296	0.023935	0.996145	24.14 dB
Kalman Filter	0.000615	0.014491	0.998172	27.38 dB

These results not only validate the filter designs but also provide a strong foundation for future integration of the cleaned sensor data into our pendulum digital twin. With accurate θ, $\dot{\theta}$, and $\ddot{\theta}$ values, we can simulate and visualize the physical system with higher fidelity, improving both real-time estimation and long-term predictive modeling.