Research Proposal for Open-Source Turntable: Creating a Unified Technique to Validate IMU Sensor Data

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Abstract

Inertial Measurement Units (IMUs) are critical tools in wearable motion tracking systems for biomechanical analysis. Despite recent advancements in high-frequency data acquisition ($500Hz$ - $1kHz+$), the accuracy of IMUs operating at such rates remains underexplored - particularly when validated against controlled mechanical motion. This proposal aims to design a high-frequency IMU acquisition system, develop an open-source mechanical validation jig for known-motion testing, and analyse orientation, angular velocity, and acceleration data accuracy using statistical error models. The findings will contribute to the development of high-precision, real-time wearable systems for medical and sports applications.

1 Introduction

Wearable technologies increasingly rely on inertial measurement units (IMUs) to quantify human motion. IMUs are "a cost-effective way to measure biomechanical and physiological data ... compared to laboratory gold standards" [1]. The total addressable market (TAM) for wearables grew by 23.1% from 2020 to 2021, reaching $10.28 billion [2], creating commercial pressure for faster, more reliable sensing. Hippos Exoskeleton Incorporated [3], for example, is developing a soft exoskeleton to prevent anterior cruciate ligament (ACL) injuries. An ACL rupture initiates within roughly 60 ms [4][5], while the company's proprietary actuator requires about 40ms to generate protective torque, leaving a sensing and decision-making budget of at most 20ms. The *sample time* - defined as the interval needed to acquire and preprocess one frame of IMU data - must stay within 20ms. This necessitates a sampling rate of well over 50Hz - ideally in at least the range of $500-1000$Hz, together with minimal preprocessing latency, to process multiple frames of IMU data ($10-20\times$ [6]) for accurate filtering and processing. High-frequency measurements must also be accurate so that physiological decisions are trustworthy.

Despite abundant work on IMUs sampled at ≤ 500Hz, comparatively little research investigates, or rigorously validates, IMU performance above this range ($500-1000$Hz and beyond). Higher sampling rates have been shown to reduce root-mean-square error (RMSE) [7], yet most studies benchmark IMUs against optical motion-capture systems whose limited video capturing frame rate (often 240fps = 240Hz) and marker placement errors can inflate kinematic inaccuracies to 42% [8]. Such errors obscure true IMU performance at 1kHz. Mechanical rigs outfitted with high-resolution rotary encoders achieve relative errors below 9% [9] and therefore represent a more suitable ground truth, but they have not been leveraged to characterise wearable IMUs operating at high frequencies.

In this proposal, I outline the design and fabrication of an open-source turntable to more accurately validate high-frequency IMU data acquisition. This work will contribute to the work that has been ongoing for the past year at Hippos Exoskeleton [3], which has been around injury prediction from IMU data.

2 Literature Review

Stetter et al. [10] achieved $1500 Hz$ sampling using custom IMUs. Chaaban et al. [11] used commercial Blue Trident sensors at $1600 Hz$. Seeley et al. [12] collected accelerometry at $1000 Hz$. Lapinski et al. [13] explored $1000 Hz$ for sports swings. Fan et al. [7] found that increasing the sampling rate of IMU sensors beyond 100Hz significantly reduced the root-mean-square deviation of the data collected from them.

Most validations rely on optical motion capture [14] [15], which suffers from soft tissue artifact (STA) and marker misalignment. Seel et al. [16] examined rate effects on joint angles using optical comparisons. However, Vox et al. [8] measured an inaccuracy of up to 42% in the measurement of joint angles using an optical system. Yi et al. [17] identified that there was an error in IMU measurements, and Zhang et al. [18] found that the most prominent source of errors in IMU sensors is caused by low-frequency oscillations and random walk of the gyroscope. Evidently, there is error in both optical and IMU measurements; hence, using an optical system as a benchmark to validate IMU data is not desirable.

Garcia et al. [19] and Hall et al. [20] used mechanical rigs but only to calibrate IMU sensors rather than to measure and compare accuracy. Both used optical rotary encoders to measure the rotational position of their mechanical systems. Jia et al. [9] found their optical rotary sensors to have an error of 9%, which is significantly smaller than the error in the optical motion caputure measurement. Taylor et al. [21] emphasise the need of mechanically testing the validity of IMU sensors, and since common IMU-based gait studies operate at $\leq 200 Hz$ [22], there is an even greater need to verify high-frequency IMU sensor data with more accurate mechanical rigs.

Carter et al. [23] are one of the very few researchers that verified IMU sensor data using a mechanical jig rather than just use it for calibration. However, they researched verified IMU sensor data at low frequencies (no more than 10Hz), not high frequency IIMU sensor data in the range of $500 - 1000$Hz, so the root-mean-square deviation-reducing effects are [7] are yet to be accurately verified with a mechanical jig.

Sensor noise and drift are characterised with Allan variance [24] [25]. Existing fusion algorithms [26] [27] lack verification over $512 Hz$ sampling. Real-time constraints are also overlooked [28] as data was stored on a microSD card and was not processed in real-time in their experiment. Further testing of how the number of IMU data frames processed [6] for different sampling frequencies affects the accuracy of the measurements is still to be desired because Zhu et al. did not explore the variation of sampling frequency in their methodology, nor did they use a mechanical jig for accurate data validation.

Gap in Knowledge: A wide range of different techniques have been found to calibrate IMU sensors, ranging from static optical ground-truth comparison [14] [15] to dynamic mechanical jigs [23], which have varying levels of accuracy. There is also far less research around high-frequency IMU data acquisition compared to low-frequency, especially the characterisation of IMU error with respect to sampling frequency. Hence, there is a two-fold gap in knowledge:

1. There is no standardised, open-source method across all of the studies for IMU data acquisition. All of the studies reviewed employ expensive commercial optical motion tracking and turntable apparatus, which makes their methodologies less accessible with limited resources, and makes it difficult to compare data obtained from different methods. An open-source mechanical IMU data acquisition platform would address both of these challenges.
2. There is little validation of high-frequency IMU data against a very accurate mechanical ground truth to verify the claim that higher sampling frequencies reduce the RMSE [7]. By designing and constructing an IMU data acquisition mechanical jig, high-frequency IMU data can be thoroughly and accurately verified.

Urgency: As wearables expand into clinical, sports and injury-prevention domains, poor and non-standardised validation of IMU data risks misinformed decisions.

3 Research Title

Open-Source Turntable: Creating a Unified Technique to Validate IMU Sensor Data

4 Project Specifics

- **Location:** University College London, Department of Electronic and Electrical Engineering
- **Setup:** IMU sensors mounted on a motorised 3 degrees of rotational freedom jig with rotary encoder reference
- **Sensors:** Commercial high-frequency IMU sensor breakout boards (specific sensors in Table 1)
- **Data:** Orientation and acceleration measured by IMU sensors vs ground truth from rotary encoders

5 Component Selection

For this research project, a preliminary selection of components is shown in Table 1.

6 Methodology

The initial, high-level methodology for the project is as follows:

- Design and construct a motorised mechanical rig with 3 degrees of rotational
  - Driven using stepper motors (Table 1)
  - Design based off a mechanical gyroscope
  - Design for manufacture through FDM printing
- Mount IMU sensors to the mechanical rig and program it to spin
  - Pre-programmed trajectory for the mechanical rig to rotate about all three axes
  - Rotation over a long period of time (at least 1 hour) to observe the effects of drift
- Log IMU and rotary encoder data
  - Data logging to a SD card through a microcontroller via the appropriate communication protocols (Table 1)
  - Rotary encoder data to be used as the ground truth
- Perform Allan variance analysis for sensor drift
- Evaluate error metrics: root mean square error (RMSE), mean absolute error (MAE), drift rates, frequency analysis

Table 1: Preliminary component selection

Subsystem	Component	Part No. / Vendor	Notes
Mechanical rig	Gimbal	Bespoke design	3 degrees of rotational freedom
Mechanical rig	Stepper motors	Nema 6 - 42	Select appropriate torque ratings
Mechanical rig	Stepper motor driver	Trinamic TMC2209	Silent, up to 2 A, UART for 1/256 microstepping config
Mechanical rig	Optical rotary encoder	E4T rotary encoder	2500 CPR, <0.15° resolution, differential TTL quadrature for noise immunity
IMU sensors	SPI IMU sensor	Analog Devices ADIS16470 breakout board	5kHz BW, ±2000°/s gyro, 16 / 32 bit, `https://github.com/juchong/ADIS16470_Arduino_Teensy/tree/master`
IMU sensors	SPI and I2C IMU sensor	InvenSense ICM-20602	1 - 32kHz sampling; 16-bit output, ± 2000°/s, ± 16 g
IMU sensors	SPI and I2C IMU sensor	Bosch BMI088	2kHz sampling; ± 24 g, ± 2000°/s
IMU sensors	SPI, I2C and UART IMU sensor	Ceva BNO085	1kHz sampling
Control system	Microcontroller	Teensy 4.1	ARM M7, 600MHz, DMA-capable SPI >20MHz, onboard MicroSD

7 Timeline

- Week 1: Design a 3-axis motorised jig, purchase components for it and purchase IMU sensors
- Week 2: Construct the 3-axis motorised jig, its control system and data logger
- Week 3: Test and calibrate the mechanical jig and IMU sensors, and an opportunity to fix any issues
- Week 4: Conduct the experiment as described in the Methodology
- Week 5: Write a report of the findings

8 Expected Contribution

This work will produce an open-source technique and turntable for unifying the methodology for IMU data acquisition, which will address the gaps in knowledge that were outlined in the Literature Review. Another aim of this work is to publish it in the **ISWC Open Wearables Conference** by **July 5, 2025**.

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