3D Mouse Documentation

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Abstract

This project presents the design and implementation of a low-cost 3D mouse using an MPU6050 inertial measurement unit (IMU) and an ESP32 microcontroller with Bluetooth Low Energy (BLE) connectivity. The device is developed as a motion-based human-computer interface capable of replacing or complementing conventional input peripherals. Raw accelerometer and gyroscope data are fused using a lightweight complementary filter, with bias correction methods applied to reduce drift and enhance stability. The processed motion data is mapped to standard Human Interface Device (HID) reports, enabling wireless cursor control and button interactions on a host computer without additional drivers. Performance metrics considered include latency, drift stability, sensitivity, and responsiveness, with emphasis on optimizing sensor calibration, real-time filtering, and BLE transmission rate. The prototype demonstrates the feasibility of developing an affordable, open-source alternative to commercial 3D input devices, highlighting both its practical usability and potential for extension into gaming, virtual reality, and advanced human-machine interaction research.

Introduction

The evolution of human-computer interaction (HCI) has increasingly emphasized devices capable of capturing three-dimensional (3D) motion, enabling more intuitive and precise control in applications such as computer-aided design, gaming, and virtual reality. Conventional input peripherals, such as standard mice and trackpads, are limited to two degrees of freedom and often require complex mappings for 3D navigation. To address this limitation, dedicated 3D mice have been developed; however, these devices are typically expensive and proprietary, limiting accessibility for research and hobbyist development. This project proposes the design and implementation of a low-cost, wireless 3D mouse using an MPU6050 inertial measurement unit (IMU) and an ESP32 microcontroller with Bluetooth Low Energy (BLE) connectivity. The device captures hand motion along multiple axes, processes orientation and displacement data in real time, and transmits HID-compliant reports to a host computer. The system aims to provide an open-source alternative that replicates the fundamental functionality of commercial 3D mice while remaining accessible for experimentation, customization, and educational purposes. The objectives of this work are threefold: (1) to develop a robust, drift-stabilized motion sensing system using low-cost MEMS sensors, (2) to implement a wireless BLE HID interface for seamless host integration, and (3) to evaluate the device in terms of latency, sensitivity, and responsiveness. This project establishes a foundational platform for further enhancements, including advanced sensor fusion, gesture recognition, and extended control capabilities, offering a practical contribution to accessible HCI research.

System Design

The proposed 3D mouse system is designed as a compact motion-sensing human-computer interface. The hardware consists primarily of two components: an MPU6050 inertial measurement unit (IMU) and an ESP32 microcontroller. The MPU6050 integrates a tri-axial accelerometer and gyroscope, providing six degrees of freedom (6-DoF) motion data. The ESP32, equipped with native Bluetooth Low Energy (BLE) capability, serves both as the data-processing unit and as the communication interface to the host device. The MPU6050 communicates with the ESP32 via the I^2C protocol, ensuring efficient acquisition of real-time motion data. The ESP32 processes this data and formats it according to the Bluetooth Human Interface Device (HID) specification, thereby emulating a standard mouse. This design eliminates the need for additional drivers on the host system, offering seamless integration across operating platforms. A minimal set of push-buttons is also incorporated to provide left- and right-click functionality, thus replicating the essential features of a conventional mouse.

Methodology

The development methodology was divided into three key stages: sensor data acquisition, signal processing, and HID report generation.

Sensor Data Acquisition: The MPU6050 inertial measurement unit provides raw accelerometer and gyroscope readings at defined sampling rates. These outputs were calibrated to remove sensor bias and scaled to physical units. For this study, the accelerometer was sampled at 1 kHz, while the gyroscope was sampled at its maximum supported rate of 8 kHz. The acquired data formed the basis for subsequent filtering and motion estimation.

Signal Processing: Raw sensor readings are inherently noisy and prone to drift. To mitigate these issues, a complementary filter was implemented to fuse gyroscope and accelerometer data, yielding stable orientation estimates. Drift stabilization techniques, including bias compensation, were incorporated to reduce cumulative integration error. The processing pipeline first acquired raw samples at 1 kHz, which were averaged over an interval determined through Allan variance analysis to suppress high-frequency noise. Stochastic Calibration was then applied to correct sensor counts, followed by optional conversion to physical units. The processed values were truncated for stability and mapped to cursor pixel displacements before being transmitted as control commands. This stage ensured that IMU-derived orientation and motion data were both stable and responsive.

HID Report Generation and Transmission: The processed orientation and motion values were mapped into displacement commands along the X and Y axes. The ESP32 microcontroller encoded this information into HID-compliant reports, which were transmitted over Bluetooth Low Energy (BLE) to the host device at fixed intervals. Button press events were also incorporated into the HID reports, enabling standard mouse functionality. This methodology emphasized low latency, noise suppression, and BLE connection stability, which are critical for practical 3D input device performance.

Implementation

The implementation phase comprised both hardware integration and firmware development, followed by preliminary validation of the prototype system.

Hardware Integration

The MPU6050 was interfaced with the ESP32 microcontroller via the I^2C protocol, with pull-up resistors on the SDA and SCL lines to ensure reliable communication. Two push-buttons were connected to general-purpose input/output (GPIO) pins configured with internal pull-up resistors, enabling left- and right-click inputs. Power was supplied through a USB interface, with an optional battery connection provided to support portable operation.

Firmware Development

The firmware was developed in C++ using the Arduino framework. During system initialization, the MPU6050 was configured and continuously polled for motion data. Calibration routines were implemented at startup to correct sensor bias offsets. A complementary filter was executed in real time to estimate orientation, and a sensitivity scaling factor was incorporated to adjust cursor responsiveness. For communication, the ESP32 was configured as a Bluetooth Low Energy (BLE) Human Interface Device (HID) using the `BLEHIDDevice` library. The HID report descriptor was customized to support two motion axes and three mouse buttons, allowing the device to be recognized by the host system as a standard mouse without requiring additional drivers. Continuous HID notifications were transmitted at a fixed interval to provide smooth cursor updates.

Prototype Validation

Initial validation confirmed reliable pairing between the prototype and a host computer, with functional cursor control achieved. The system demonstrated low-latency data transmission and basic usability, establishing a baseline for subsequent performance evaluation through numerical testing and experimental trials.

Error Modeling

The implementation of theoretical concepts in real-world systems requires careful consideration of practical limitations, as no mathematical model can perfectly describe sensor behavior under all conditions. Various irregularities, such as manufacturing imperfections, temperature fluctuations, and electronic noise, introduce errors into the sensor readings. To adapt to these challenges, calibration and error modeling techniques were applied to characterize and mitigate these effects.

Stochastic Calibration (Allan Variance)

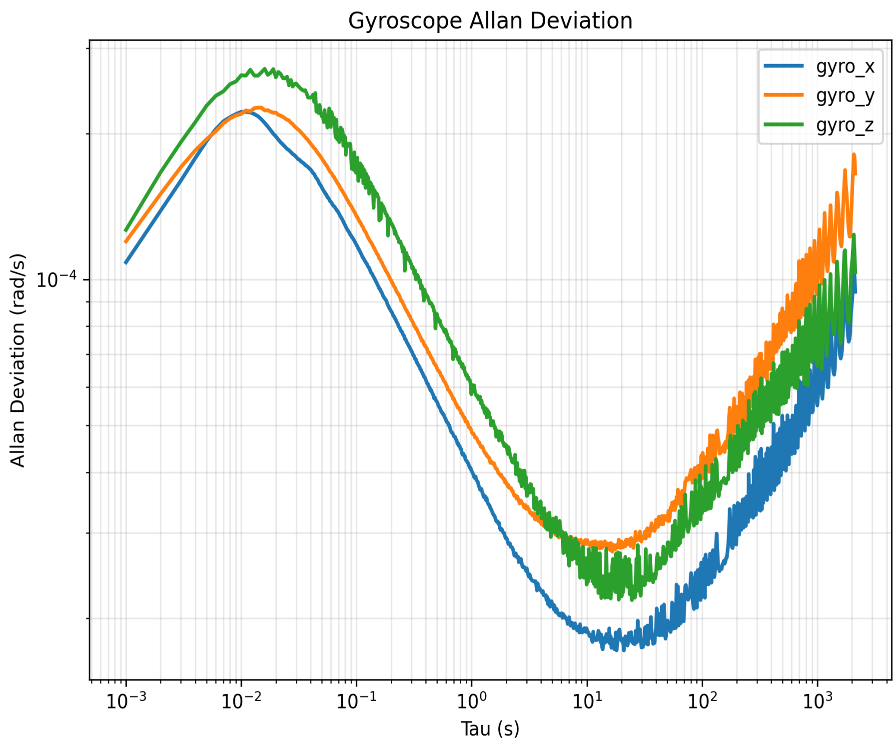
Allan variance analysis was employed to characterize the stochastic error components of the inertial sensors. This method quantifies how measurement accuracy changes as data is averaged over different time intervals. At shorter averaging times, variance decreases due to the suppression of high-frequency noise. However, beyond a certain point, the variance begins to increase again as long-term bias drift dominates.

For the present application, longer averaging times can be tolerated compared to higher-grade accelerometers, since the required bandwidth is limited to motions below 10 Hz. Thus, Allan variance provided a suitable framework to determine optimal averaging intervals for data acquisition and stability assessment.

Formally, for a time series x_k sampled at intervals of T_0, the cluster size m (number of samples per cluster) defines the averaging time $\tau = mT_0$. Let M be the number of non-overlapping clusters, and $\bar{y}_i$ represent the mean of the i-th cluster. The Allan variance for averaging time τ is given by:

$$\sigma^2(\tau) = \frac{1}{2(M-1)} \sum_{i=1}^{M-1} (\bar{y}_{i+1} - \bar{y}_i)^2$$

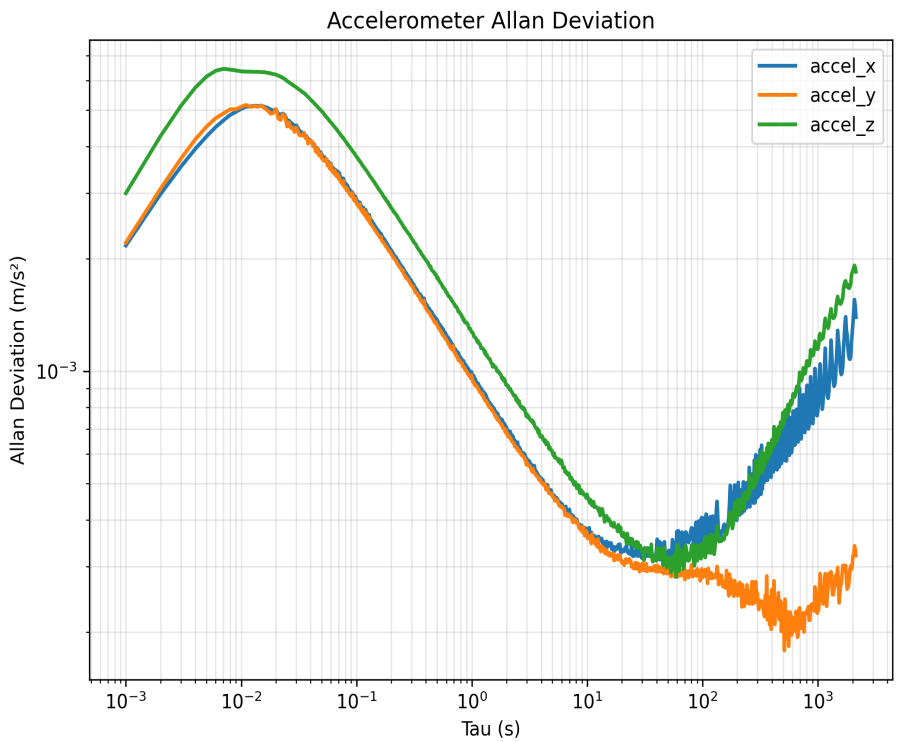
Gyroscope Allan Variance:



Parameter	**X**	**Y**	**Z**
ARW $[rad/s/\sqrt{Hz}]$	3.428×10^{-6}	3.786×10^{-6}	3.999×10^{-6}
Bias Instability [rad/s]	1.715×10^{-5}	2.743×10^{-5}	2.179×10^{-5}
Averaging Time [s]	20.97	16.60	24.62
Bias Drift Onset [s]	59.95	61.72	50.32

Table 1: Extracted Allan variance parameters for the gyroscope.

Accelerometer Allan Variance



Parameter	X	Y	Z
VRW $[m/s^2/\sqrt{Hz}]$	6.861×10^{-5}	6.988×10^{-5}	9.472×10^{-5}
Bias Instability $[m/s^2]$	3.044×10^{-4}	1.787×10^{-4}	2.810×10^{-4}
Averaging Time [s]	48.87	511.98	59.08
Bias Drift Onset [s]	95.62	519.50	131.81

Table 2: Extracted Allan variance parameters for the accelerometer.

Deterministic Calibration

Accelerometer 6 Point Calibration

Here we find the 3×3 scale/misalignment matrix M and a 3×1 matrix b such that:

$$a_{True} = M(a_{raw} - b)$$

where a_{true} corresponds to the expected acceleration when the sensor is stationary and aligned with gravity. In this configuration (i.e., with the mouse body held stationary and oriented such that its sensitive axis is aligned with the gravitational vector), the accelerometer should ideally report a magnitude of

$1g$. The six-point calibration procedure yielded the following calibration matrix M and bias vector b:

$$M = \begin{bmatrix} 6.08997382 \times 10^{-5} & 7.41227306 \times 10^{-7} & 2.03088121 \times 10^{-6} \\ 1.69669384 \times 10^{-6} & 6.12865742 \times 10^{-5} & -1.71520618 \times 10^{-7} \\ -3.16142589 \times 10^{-7} & 4.30764171 \times 10^{-6} & 6.00314277 \times 10^{-5} \end{bmatrix}$$

$$b = \begin{bmatrix} -0.05525702 & 0.01076481 & -0.03638963 \end{bmatrix}$$

$$bias_{gyro} = \begin{bmatrix} -0.05525702 & 0.01076481 & -0.03638963 \end{bmatrix}$$

Following this calibration, additional fine-tuning will be applied to achieve sub-degree accuracy and improved stability.

Future Work

Several improvements remain to be addressed in order to further enhance sensor performance. One key aspect is temperature compensation, which can mitigate thermal drift effects on both accelerometer and gyroscope measurements. In addition, gyro calibration can be performed during periods when the accelerometer indicates no motion, with consecutive gyro readings averaged over the optimal interval to establish an updated zero-rate reference.

The deterministic calibration currently assumes a linear response that was used in the calibration as ($a_{True} = M(a_{\text{raw}} - b)$), whereas in practice sensor behavior is often nonlinear. Future work should therefore focus on mapping the nonlinear sensor response to an equivalent linear model. Cross-axis alignment, another source of systematic error arising from manufacturing imperfections, should also be corrected to improve accuracy prior to the application of sensor fusion algorithms.

It is noteworthy that many of these compensation and calibration techniques are already implemented internally in newer-generation IMUs such as the BMI160 and ICM-426xx series from TDK/InvenSense. For applications requiring higher precision than the present prototype, these calibration steps can be performed with greater accuracy at the library or algorithmic level to meet specific performance requirements.

Discussion

The calibration and error modeling results highlight the inherent limitations of the MPU6050 sensor package while also demonstrating the effectiveness of the applied corrections. The six-point deterministic calibration successfully reduced static bias and scale factor errors, producing a calibration matrix that aligned the accelerometer outputs with the expected 1 g reference when stationary. This step was essential to establish a consistent baseline for orientation estimation.

The stochastic characterization using Allan variance provided further insight into the noise properties and drift behavior of the IMU. The gyroscope exhibited angle random walk (ARW) on the order of 10^{-6} rad/$\sqrt{s}$ and bias instability between 1.7×10^{-5} and 2.7×10^{-5} rad/s, with drift becoming dominant after approximately 50–60 s. The accelerometer demonstrated velocity random walk (VRW) values on the order of 10^{-5} m/s^2/$\sqrt{Hz}$ and bias instabilities in the range of 1.8×10^{-4} to 3.0×10^{-4} m/s^2, with drift onsets between 95 s and 520 s depending on axis. These results confirm that while short-term noise can be effectively reduced through averaging, long-term drift remains a limiting factor for extended operation without external correction.

Together, these findings indicate that the prototype 3D mouse is suitable for short-term interactive tasks, where motions are constrained within tens of seconds, but less reliable for applications requiring long-duration stability. The behavior is consistent with expectations for an older consumer-grade IMU such as the MPU6050, which lacks built-in temperature compensation and advanced calibration features found in newer devices. Nonetheless, the calibration framework and Allan variance analysis provide a valuable foundation for improving performance through sensor fusion, periodic re-zeroing, or hardware upgrades.

Conclusion

This project demonstrated the design and implementation of a low-cost, open-source 3D mouse using the MPU6050 IMU and ESP32 microcontroller with BLE support. A complete calibration workflow was applied, including deterministic six-point calibration and stochastic characterization via Allan variance. These procedures quantified the error sources in the IMU and established the limits of its performance in terms of bias stability, noise density, and drift onset.

The results show that the MPU6050 is capable of providing stable orientation estimates over short time horizons, but its long-term stability is constrained by bias drift. These findings align with the known limitations of first-generation consumer MEMS sensors. For practical use, the device is effective in demonstrating proof-of-concept 3D motion control, with the potential for educational and research applications.

Future work should incorporate temperature compensation, dynamic bias correction during stationary intervals, and nonlinear response modeling to further reduce error. In addition, migrating to newer IMUs such as the BMI160 or ICM-426xx would enable higher accuracy and stability by leveraging on-chip calibration and drift compensation. Ultimately, this project establishes a baseline system that can be extended into more robust human-computer interaction devices through improved hardware and advanced sensor fusion algorithms.