An Accessible, Low-Cost method for Gait Monitoring with a Raspberry Pi and MPU 6050: Proof of Concept

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Summary

Gait deviations are common in aging populations and those with neurological or musculoskeletal disorders, leading to reduced independence and higher healthcare costs. Even though optical motion-capture systems deliver the accuracy necessary for kinematic analysis, the cost associated with it restricts the usage in laboratory settings. We developed a low-cost, wearable gait measuring device that can be held in the hand, utilizing a Raspberry Pi 5 and an MPU6050 IMU. The system recorded six motion features from an inertial measurement unit and compared walking trials against a user-specific baseline using a Euclidean distance metric. Unlike camera-based or smartphone-dependent systems, our proposed device operates independently of external infrastructure and is designed to support patient-specific calibration using minimal computational resources. We hypothesized that gyroscope-based motion features would be more sensitive than

accelerometer features for distinguishing deviations from normal gait. The tool has the potential to enhance remote gait monitoring, rehabilitation, as well as the early detection of conditions of gait abnormalities, thus improving the quality of life for patients suffering from gait disorders. Preliminary testing using simulated gait conditions demonstrated greater variability in gyroscopic features compared to accelerometer features, with correct classification in approximately 75% of tested conditions across multiple simulated gait scenarios.

Introduction

Mobility impairment, persistent gait deviations that limit and/or pose a danger towards someone's walking posture, is a particularly prominent issue among aging and physically disabled populations worldwide. Gait disorders, which can be defined as sustained abnormalities in walking, are identified as some of the most frequent signs of neurological disorders, musculoskeletal conditions, as well as the consequences of traumatic conditions. These conditions significantly reduce the quality of life while also adding to the cost of healthcare, particularly in relation to the utilization of assistive devices, physical therapy, as well as surgery. The availability of low-cost, timely, and personalized systems for monitoring gait remains a challenge, even as technology advances. Most available systems in the market today tend to be large, costly, and not suitable for domestic use, contributing to the large number of non-diagnosed individuals. Various attempts to analyze gait over the last decade exist in the form of studies. For example, 3D-motion capture systems such as Vicon have been used to replicate joint movement in biomechanics laboratories, and sensor platforms on treadmills provide controlled test environments for analyzing lower limb kinematics (9). In the year 2022, a systematic review in the "Sports Medicine - Open" journal reported that wearable technology offers a practical solution for runners, as well as physical trainers, to analyze the gait cycle, bypassing the issues associated with the existing techniques in use today (7). The review explained that systems using accelerometers, gyroscopes, magnetometers and pressure-sensing insoles can record spatiotemporal and kinematic measures and benefit from ease of use and affordability (7)(3). This is in direct alignment with the present research design.

In another similar study in Sensors, the feasibility of applying smartphone technology to gait monitoring was trialed. Results indicated that an affordable marker-based setup utilizing smartphones was enough to detect the spatiotemporal patterns of a human walk with a remarkably high level of accuracy and so further in line with the shift towards more economical options (1). In a standalone validation study, portable motion capture systems were found to be highly correlated with established reference hardware, which translated to small errors with an RMSE of 0.05-0.17 m/s for gait speed and 0.02-0.08 m for step and stride length thereby ensuring their capacity to yield clinically relevant measurements (8).

Nevertheless, despite advances in technology, a comprehensive review in Sensors cautioned that numerous studies do not adequately address users' physical, physiological, and social needs when designing or even evaluating the tech, reflecting usability concerns and long-term uptake (12). There is, nevertheless, a positive consensus; the aforementioned Sports Medicine review confirmed that wearable technology proved reliable for detecting running gait when checked against current reference standards (7). Combined, these investigations provide a solid foundation for developing individualized, affordable, and modular gait diagnostics, especially in a context where patient comfort and affordability are of utmost importance.

The existing research work emphasizes the use of wearable technology like Inertial Measurement Units (IMUs) and pressure-sensing insoles in monitoring gait while outdoors, which has been largely attributed to the use of mobile applications. Artificial intelligence-based approaches to classifying gait patterns, including neural networks and Support Vector Machines (SVMs), have been investigated by research groups. Yet, these systems tend to be dependent on extensive datasets, proprietary software, or expensive hardware configurations, constraints that may hinder widespread usage, especially in low-resource or rural communities. Although existing research has laid significant groundwork, it lacks the scalability, adaptability, and open-source approach that the following work aims to address. Many existing devices lack real-time classification capabilities, are not tailored to the specific wearer's physiology, or are so obtrusive as to be impossible for daily use.

The system addressed the gaps by combining a lightweight MPU 6050 accelerometer and a Raspberry Pi 5. The setup enables real-time classification of gait cycles with minimal hardware resources and power consumption. Furthermore, it provides modularity and expandability, allowing the device to be modified for various age groups, genders, or specific medical conditions. Its affordability and versatility make it especially suitable for remote measuring uses, monitoring of physical therapy, and early detection of neurological disorders. In this paper, we specified the implications and building process of a low cost, accessible gait monitoring device powered by a Raspberry

Pi and MPU 6050 as well as the ability of screening clinical abnormalities and rehabilitation are detailed.

This article is organized as follows: the hardware and software components, including calibration procedures, sensor integration, and 3D design considerations, are described in the first half. Then, data collection and modeling procedures were presented, including the method by which gait cycles were recorded and classified using trial-based optimization. A proof-of-concept case study is simulated to assess device responsiveness and accuracy for various abnormal gait patterns. The design decisions, limitations, and broader implications of the study are considered under the Discussion section. Finally, evaluations on future directions for work on improving measuring accuracy, real-world testing on diverse populations, and eventual use in clinical practice were determined. We examined the development of a low-cost, handheld gait monitoring device using a Raspberry Pi and an accelerometer. We hypothesized that comparing real-time inertial sensor data to a personalized baseline would allow a low-cost Raspberry Pi–based system to identify deviations from normal gait.

Results

As depicted in Figure 2, significant deviations were recorded in the gyroscope values, particularly in g_x and g_y.

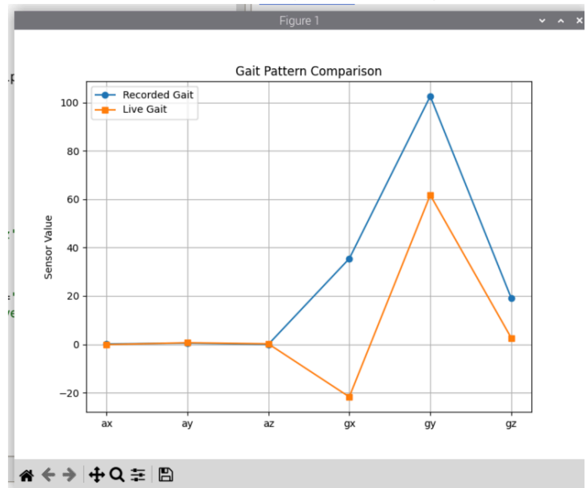


Figure 2: Example of raw data from Test 1: Comparison of gait mean vectors for six features

The g_x and g_y values had the most variability, indicating rotational asymmetry during abnormal walking.

Device setup:

Our gait monitoring device was made up of the Raspberry Pi 5 and the MPU-6050 accelerometer-gyroscope module which was interconnected using the I2C bus. Power was supplied via the Pi's 5V rail, and logic-level data was communicated through the GPIO pins. Specifically, the VCC, GND, SCL, and SDA pins were soldered with permanently fixed jumper wires. Figure 1 illustrates how the entire system was mounted on a rig, allowing for secure attachment to the lower leg with accurate forward-facing alignment.

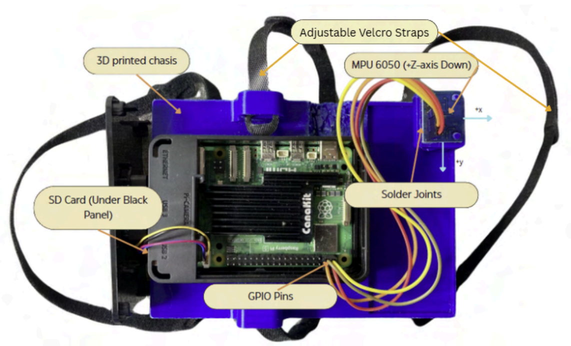


Figure 1: Hardware photo of Raspberry Pi connected to MPU6050

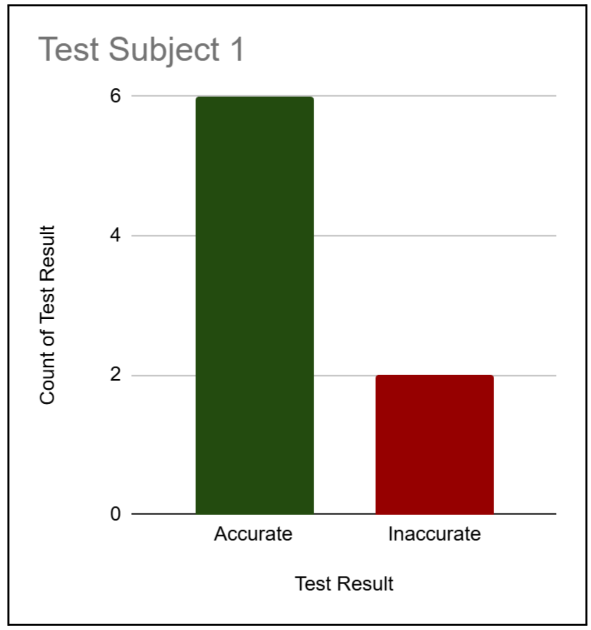
We designed this device in a way that calibration was specific to each user: their gait was meant to be recorded only once to generate a “baseline” mean vector. When comparing a new gait walk, the system calculated a new mean vector and performed Euclidean distance comparison against the baseline.

The holistic results were recorded in Figures 6 and 7, showing an estimated 75% accuracy from a total of 12 trials, 8 with test subject 1 and 4 with test subject 2.

Test Subject 1: Walk 5 steps forward with Person 1.

Figure 6. Representative Test Results for the first control group

Flowchart illustrating the processing sequence used by the system, including sensor initialization, signal filtering, step detection, feature extraction (ax, ay, az, gx, gy, gz), baseline calibration, and Euclidean distance based gait classification for each simulation in test 1.

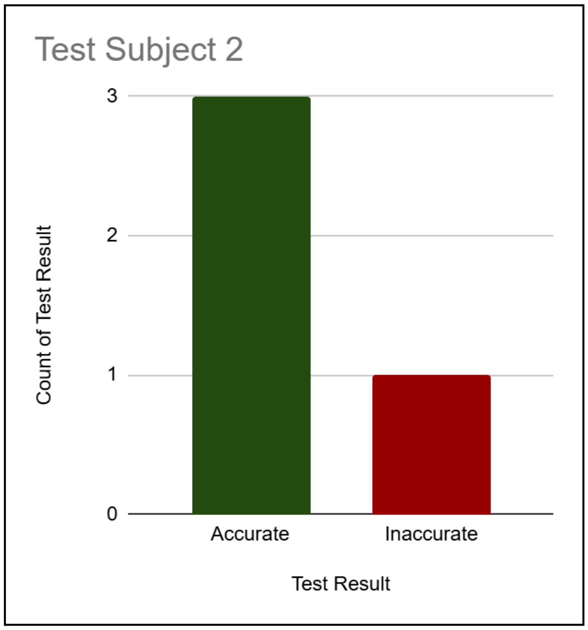


(TS 1)

Test Subject 2: Walk 3 steps forward with Person 2.

Figure 7. Representative Test Results for the second control group

Flowchart illustrating the processing sequence used by the system, including sensor initialization, signal filtering, step detection, feature extraction (ax, ay, az, gx, gy, gz), baseline calibration, and Euclidean distance based gait classification for each simulation in test 2.



(TS 2)

Case Study

The difference between the recorded and live gait motion can be seen in Figure 2, where the greatest variation can be observed in the gyroscopic data points (g_x and g_y), distinguishing the irregular rotational movement throughout the live experiment. The recorded gait exhibited a more defined trajectory, in contrast to the live gait, which has been attenuated. The sample size included 2 different people with different physical capabilities (5 ‘8 athletic male [Test 1] and 5 ‘1 sedentary female [Test 2]) with 8 different situations (refer to appendix for more information) for Test 1 and 4 different situations with Test 2 with correct classification in approximately 75% of tested conditions in this limited sample. Using a subject baseline, the MPU made a direct comparison to the tested net movement and the recorded control group net movement. The specific simulation of the testing process is described in the appendix.

In order to ascertain if there exists an abnormal gait, the software calculated the Euclidean distance between the mean of the current walk and the mean of the base line. During the testing phase, the default classification threshold was set to 60.0, based on an iterative trial-and-error approach. Gait sessions producing distances below this value were considered normal, while higher distances were flagged as abnormal.

Discussion

We developed and deployed a small-scale, proof-of-concept, cost-effective, portable gait monitoring system based on a Raspberry Pi 5, MPU6050 accelerometer/gyroscope, and threshold-based gait classification. This study was motivated by the high expense and sophistication of commercial gait analysis systems, which remains inaccessible for patients in low-income or rural areas. Employing a modular, programmable, and entirely open-source configuration, this study demonstrated that significant inferences regarding gait cycles are possible with only six movement features: a_x, a_y, a_z, g_x, g_y, and g_z, without the necessity of complex or invasive laboratory-level equipment. Rather than depending on large amounts of training data, the system measured new gait recordings against a personalized baseline by Euclidean distance, thereby providing an efficient method for anomaly detection. This enabled the application of a personalized diagnostic threshold for future anomaly detection. The justification for this approach stems from the simplicity of step detection and real-time processing compatibility with the Raspberry Pi. Utilization of the high-pass filter, with an empirically determined cutoff at 0.8gs, was a critical decision that allowed us to remove gravitational impact and filter linear motion. The implementation of cooldown logic and thresholding also served to sense steps more precisely eliminating noise from small movements or spurious triggering.

An accelerometer-based handheld gait monitoring device capable of identifying abnormal gait patterns in real time. While commercial wearables like Apple Watch and Fitbit are prevalent, they were within 3% of real values 71% and 51% of the time, respectively (Fuller, 2020). However, smartphone-based gait systems have shown great potential in the past, with correlation coefficients ranging from r = 0.77 to 0.98 and test-retest reliabilities of up to ICC = 0.95 when compared to inertial sensor systems (Howell, 2019). Similarly, a systematic review of wearable gait studies found that 77 out of the 131 articles examined explored their real-world application, increasing their growing validity in clinical research (Mason, 2022). This project proposed a low-cost system entailing a Raspberry Pi and accelerometer-based handheld gait monitoring device capable of identifying abnormal gait patterns in real time. This device was designed with an emphasis on accessibility, versatility, and patient-specific calibration, presenting a practical solution to a significant biomedical need.

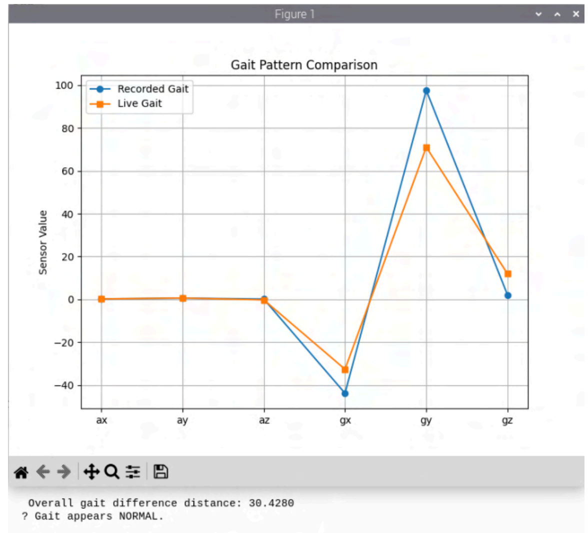


Figure 3: Comparison of Raspberry Pi 5 with other circuit boards

The trials resulted in an overall accuracy of 75%, meaning of all the simulations ran, the system was able to correctly identify abnormal gait 9/12 times. Minimum divergence in the features was noted in the trials in which the system indicated the classification outcome as NORMAL. Simulated abnormal gait trials were also taken to note the maximum divergence in the features, especially for gyroscopic features, and the system indicated the classification outcome as abnormal. The normal gait trials indicated that the live gait feature vector was aligned with the baseline feature vector for different gait trials, indicating a lower value for the Euclidean distance metric and resulting in the classification outcome as normal.

First, the MPU6050 sensor, while being lightweight and affordable, had a finite upper limit for its acceleration and gyroscopic readings, often saturating or plateauing at high values. Euclidean distance was selected as a computationally efficient metric for baseline comparison, though future implementations may incorporate learning-based classifiers to capture more complex gait patterns. A more expensive and accurate accelerometer may be used to mitigate errors; however, this conflicts with the idea of a cost-effective mechanism.

Real-time feedback mechanisms were also lacking in the system; it relied solely on post-walk analysis to announce if a gait is normal or abnormal. Limited user testing was another limitation with n=2, recommendations for the future suggest an n-size of 15-30 and increased diversity. Testing was conducted using simulated gait conditions on a limited number of participants, which constrains generalizability and motivates future validation on larger and more diverse cohorts. The present prototype was also physically restricted, e.g., by its size, absence of wireless transmission modules, and by its manually controlled parameters rather than adaptive calibration. Lastly, there were no long-term measurements made to determine gait stability during changing walking conditions, surfaces, or levels of fatigue, each of which will impact accuracy.

Although this project did not use a machine learning model, the program was designed with future ML integration in mind. The current architecture supports data acquisition, preprocessing (gravity filtering), step segmentation, vector averaging, and real-time visualization. Once TensorFlow Lite or a similar library is integrated, these same six features can be passed into a trained classifier (e.g., Random Forest) to return probability scores for various gait types. A key advantage of the designed system was modularity; replacing the Euclidean metric with a model prediction required minimal changes. ML algorithms have been used in the past to analyze gait cycles by feeding sensor capabilities like IMU or EMG features and trains like HMMs, SVMs, or CNN/LSTMs to identify gait types and detect abnormalities (Park, 2023).

In addition, the system supported synthetic data generation for future model training. Users can simulate abnormal gaits (e.g., limping, foot dragging) to collect labeled data manually. Each walk was stored and timestamped, allowing easy export for off-device training. The computational process is fast, with classification completed within 23 seconds after walking.

This program also has potential for future data management and hardware integration improvements. One of the follow-up steps will be to actually put in place a specific machine learning system. Synthetic gait data could also be used to supplement the training set artificially. This includes generating modelled patterns of motion like limp-caused vertical asymmetry or irregular cadence by altering captured data to simulate unnatural gait cycles. This would enable the model to train under a vast variety of conditions, even before actual patient testing. These insights suggest that a future ML classifier could assign different weights to each feature based on observed variability and diagnostic relevance, which bolsters cadence detection accuracy.

Recent advances in wearable inertial measurement units (IMUs) have enabled moderate agreement with optical systems for gait analysis, offering portability and affordability. Another area for improvement concerns hardware optimization: substituting the Raspberry Pi with an even more compact board, like the Raspberry Pi Zero 2 W or ESP32, incorporating Bluetooth capability to enable real-time data transfer, and developing a mobile interface for seamless remote monitoring. Additionally, the physical form factor itself can be optimized using 3D printing to enable more ergonomic and comfortable use during typical patient activity. Follow-up trials should involve a wider population of participants with variations in age, gender, body mass, and walking conditions to validate the accuracy and durability of the device. Alternative locations for sensors, i.e., ankle, shin, or hip, must also be investigated to enhance sensitivity and minimize variability caused by inconsistent fixtures. Eventually, the device can be calibrated not just to detect abnormality but to quantify risk, providing scores or risk factors based on how much a live gait deviates from a person's normal baseline. Such a diagnostic would be invaluable in preventative medicine, rehabilitation monitoring, or even athlete performance assessment. Finally, the inclusion of data logging for longitudinal monitoring across weeks or months would render this device a holistic personal gait tracker, potentially alerting users to early changes even before they are clinically apparent. Future steps would be to expand upon the experiment with more participants and greater diversity, investigate long-term gait changes with different walking surfaces and fatigue, experiment using machine learning with TensorFlow Lite for probabilistic classification and also improve the hardware optimization for miniaturization and wireless communication.

Methodology and Materials

This study uses a Raspberry Pi 5 from Canakit as the central computing unit, interfaced via I2C with an MPU6050 accelerometer-gyroscope sensor module that measures three-axis motion. All gait data were collected from consenting participants using non-invasive sensors, and no personally identifiable information was recorded. The Python control program script, developed via the Thonny IDE, uses libraries such as smbus, numpy, matplotlib, and csv for sensor interface, data analysis, and visualization. The power source used is an Anker Power Bank (PowerCore 10K),Compact Travel-Ready 10,000mAh Battery Pack with PowerIQ Charging Technology, 5V/3A connected to a 3-foot black USB-C charging cable to power the Pi. The MPU6050 sensor is calibrated using dedicated I2C registers, and the system reads continuous acceleration and gyroscopic data filtered by a high-pass filter (with a cutoff frequency of 0.8) to eliminate gravitational effects and focus on linear motion. The step detection algorithm reads lateral y-axis linear acceleration with a user-adjustable threshold (default 0.3g) to tally occurrences of steps. Upon detecting the predetermined number of steps, the system records six parameters, a_x, a_y, a_z, g_x, g_y, g_z, along with their timestamps, subsequently saving this data to a CSV file. Users have the option to perform an additional walking test for comparison, in which the system computes the Euclidean distance between real-time data and stored mean vectors for the analysis of gait abnormalities. The enclosure of the module was 3D printed using dark blue, medium-grade PLA plastic for a compromise between durability and comfort. The cost of the entire system stands at around $150 USD in comparison to other gait measurement techniques, which cost up to $200,000 USD. The modularity makes it easy to make future adjustments to fit various body types and has the potential to leverage additional 3D printing technology for added precision. Despite screening multiple materials, including the implemented tin and lead compound, the soldering process was efficient with a 60/40 tin lead solder, permanently attaching the pins to the VCC, GND, SCL, and SDA pins on the MPU6050. The flow-chart detailing the algorithm performed in the proposed system for processing the sensor values, from filtering to classification, has been depicted in Figure 4 below.

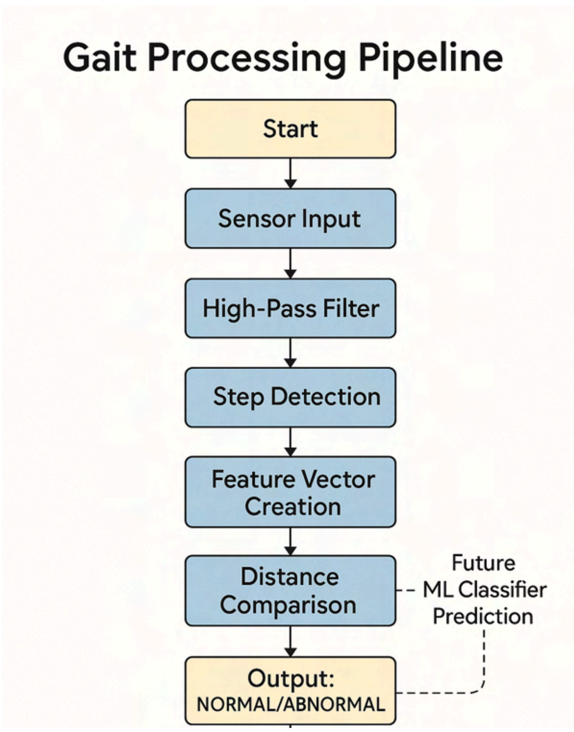


Figure 4: Gait processes illustration

Operational Procedures

The operation begins by initializing the MPU6050 over I2C and applying a high-pass filter optimized empirically through trial-based error (iteratively increasing the filter by 0.1 for enabling the pi to comfortably detect a step), serving as a measure of sensitivity (= 0.8). The system measures three axes of acceleration (ax, ay, az) and three axes of angular velocity (gx, gy, gz) in the sensor's local frame (x = forward, y = lateral, z = vertical). After obtaining these six measures, the system applies user-specific calibration and detects gait anomalies by comparing real-time data to a personalized baseline via a Euclidean distance metric. The user selects a threshold (e.g., 0.4g) and specifies the number of steps to be recorded. During recording, the y-axis linear acceleration is monitored to detect distinct steps using a peak-detection logic combined with a 10-frame cooldown. Once sufficient steps (user-defined parameter with 3-10 steps on average) are collected, the device saves all six features a_x, a_y, a_z, g_x, g_y, g_z, along with timestamps into a CSV file. The a_x, a_y, a_z values specify the accelerometer linear values, while the g_x, g_y, g_z values specify the highly sensitive gyroscopic numerical values. These values have no initial unit and require specific code to manually calibrate them to a set unit of measurement.

The sensitivity of each feature was evaluated during 10 repeated sessions. The g_x, g_y, g_z were the most reliable for step recognition, while the insensitive a_x and a_y captured net movement across the x and y axes from dragging or limping. We designed the system so that it operates through a menu command-line interface that guides the user through recording, comparing, and managing gait data. The terminal of the software has been depicted in Figure 5, which has a text interface where the user can easily switch between the main tasks of gait recording, comparison, and management. The interface requires the user to enter a choice from the menu.

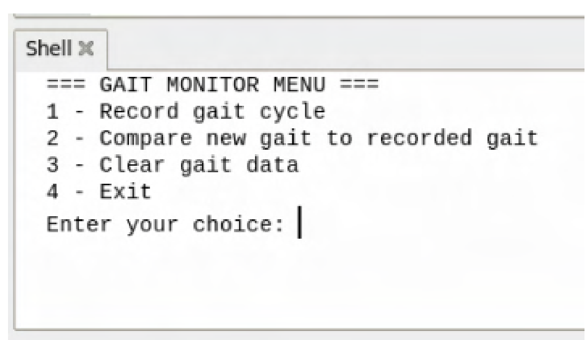


Figure 5: Screenshot of terminal interface on the user side

These results represent a clear sensitivity to linear and rotational gait deviations and support the utility of this approach in the early-stage detection of gait anomalies. Also, this system offered personalized calibration, a modular hardware design, and ease of use, thus being a feasible candidate for real-world deployment in various clinical and non-clinical settings. Its low cost and open-source architecture further make it highly accessible, especially in resource-poor settings lacking traditional gait laboratories. The current iteration uses rule-based classification while the architecture is specifically designed to accommodate machine learning algorithms on future upgrades, including the generation of synthetic data and TensorFlow Lite deployment, offering the possibility of higher accuracy in classification, dynamic risk profiling, and extended compatibility in the population. This device has practical applications in remote diagnostics, physical therapy monitoring, and preventative screening for neurodegenerative diseases like Parkinson's. Considering the continued progress to personalization and accessibility in health care, contributes to scalable biomechanical systems which ultimately empower clinicians and patients alike.

Note: IRB Human participants, informed consent forms, and risk assessment forms were acquired and approved on 12/5/2025.

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Appendix:

Link to Github repository for code used in System:
https://github.com/Snch579/Gait-Detection-Code/blob/main/README.md?plain=1

Raw data is available upon request