

A Wearable Sensor-Based Framework for Quantifying Imbalance in Parkinson's Disease: A Proof-of-Concept Study Using Biomechanical Analysis and OpenSim Modeling

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ABSTRACT

Parkinson's disease (PD) is the second most common and dangerous progressive neurodegenerative disease, affecting motor symptoms and causing more than 329,000 global deaths annually. Current methods to diagnose and understand impairments in motor and cognitive function can cost hundreds of thousands of dollars annually, making it difficult for individuals in low-income and rural communities to access adequate technology and equipment. Musculoskeletal simulations and a wearable sensor present an affordable and accessible solution to track movement qualities quantitatively in real-time to analyze movement during daily tasks. In this study, a neurologically healthy adult and a patient with Parkinson's disease were examined on their postural stability across 3 trials, each repeated thrice, where the normal adult was used as a negative control and the Parkinson's patient as the experimental participant (PD participant). The results showed that the PD participant demonstrated peak pitch displacement approximately 279% greater than the control during the standing trial (22 vs. ~5.8), and a sustained lateral roll deviation peaking at 37° to the left during walking compared to a maximum of approximately 2° to the left in the control. The time taken to complete each trial shows that the PD participant took longer on the standing and walking trials (+3.48 s and +7.54 s, respectively) but terminated the twisting trial earlier than the control due to instability. This study provided a proof-of-concept of the effectiveness of small wearable systems in quantifying movement characteristics in Parkinson's patients, presenting applications as an inexpensive and large-scale tracking system.

Keywords: Parkinson's disease, motor and cognitive function, imbalance, musculoskeletal simulation, wearable sensor

1. INTRODUCTION

Parkinson's disease (PD) poses a major threat to human health and a patient's quality of life. This is a progressive neurodegenerative disorder, the second most common of its kind after Alzheimer's disease, which is caused by the loss of dopaminergic neurons in the brain, resulting in symptoms such as

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imbalance, tremors, rigidity, poor posture, and impaired ability to perform basic movements (Kwon et al., 2022). More than 10 million people around the world have PD, and over 1.1 million people in the United States have PD, and nearly 90,000 new cases are diagnosed each year; the likelihood of developing PD rises significantly with age, and men are about 1.5 times more likely to be affected than women (Parkinson's Foundation, 2024). In the United States, the direct and indirect cost of PD in 2024 was \$82.2 billion and is expected to increase with age (The Michael J. Fox Foundation, 2026). Disruption of dopamine signaling is central to the breakdown of stable, coordinated motion and is known to play a critical role in movement initiation, wakefulness, attention, cortical arousal, and the allocation of cognitive-motor resources (Dong et al., 2022; di Bello et al., 2024). This impairment is associated with a general lack of motor control and coordination, so balance is evident in almost every activity of daily living (Chu et al., 2023). Patients with advanced disease are at the highest risk of experiencing dangerous levels of instability because of the progressive loss of dopaminergic neurons, which starts before widespread neuronal failure occurs (Chu et al., 2023). This condition poses significant problems, since poor postural control has been linked to increased fall risk and serious complications in those who have it (The Michael J. Fox Foundation, 2026). Postural instability and gait impairment are among the many PD motor symptoms that have been most widely studied and thus are most strongly linked to loss of independence (Schlachetzki et al., 2017). These impairments also represent one of the best predictors of recurrent falls and functional independence in people with Parkinson's disease (Bloem et al., 2004). A number of assessment technologies have been investigated to meet the challenges of PD. Clinical rating scales, optical motion capture, and force-plate posturography are all used for traditional assessment methods that have been effective in quantifying motor impairments (Schlachetzki et al., 2017). However, these approaches tend to have high equipment demands and operational costs, reducing their applicability to broader use, particularly in resource-constrained environments, such as rural and low-income communities (Salchow-Hömmen et al., 2022). For instance, gait parameters can be measured using video-based motion-capture systems, which are costly, require specialized movement laboratories, and are not readily available for routine quantitative monitoring of gait parameters for many patients who would benefit most. (Salchow-Hömmen et al., 2022). Wearable inertial sensing is a potential solution to these problems, is sustainable, and is inexpensive. This technology builds on the ability of small, commercially available triaxial gyroscopes and accelerometers to detect, quantify, and characterize body movement quality in real time (Caramia et al., 2019). In recent years, wearable sensors have been the focus of many studies for gait measurement in PD (Caramia et al., 2019; Sica et al., 2025). There is, however, a large gap in understanding the potential of wearable sensors combined with biomechanical simulation, which relates observed motion to the muscle forces that generate it, in quantifying imbalance during real-life motor tasks. The use of wearable sensors to quantify imbalance would make a tremendous contribution to the development of effective diagnostic infrastructure because sensor-based systems can be deployed in a variety of settings, including urban areas and areas where specialized equipment is not readily available. Wearable systems are smaller than conventional motion analysis laboratories and can be used in resource-limited settings to conduct large-scale monitoring operations (Sica et al., 2024). In addition, in the field of pathological gait (PD), some studies have found that musculoskeletal modeling can help interpret motor deficits (De Groote & Falisse, 2021; Delp et al., 2007); however, to my knowledge, there are no similar studies that combine wearable sensing with musculoskeletal modeling to quantify

imbalance during daily motor tasks in PD. The integration is the main novelty of the present work, since the combination of real-time sensor data with simulated muscle dynamics may be used to complement sensor-based assessment of PD motor symptoms, even though the two data sources were collected and analyzed independently in this proof-of-concept study (Delp et al., 2007). Thus, the goal of this study is to fill these gaps by designing and testing a wearable sensor-based framework to quantify imbalance in PD patients during daily activities and to show the feasibility of using OpenSim musculoskeletal modeling to characterize the muscle force patterns that underlie that imbalance. To ensure that both static and dynamic deficits are captured, the quantification of both postural and gait-related instability was studied. This is significant as other assessment techniques are known to be more sensitive to overt symptoms than subtle, and often early instability goes undiagnosed in patients (Schlachetzki et al., 2017). The selected tasks (standing, twisting, and walking) were chosen because they were commonly used in daily life, required minimal effort from the participant, and provided a variety of balance challenges (Caramia et al., 2019). To minimize the likelihood that any imbalance found would be due to the specific requirements of one motor task, three motor tasks were specifically investigated rather than only one. Overall, this study sought to investigate whether wearable sensors could detect and quantify the balance impairments in patients with Parkinson's disease (PD) and whether the level of balance impairment measured by the sensors would be systematically higher for different motor tasks that require varying levels of balance. To test this hypothesis, triaxial angular data were collected from a PD patient and the control participant during standing, twisting, and walking tasks, with and without the use of OpenSim musculoskeletal modeling, to examine their ability to quantify imbalance and the muscle force deficits associated with it. In this experiment, three motor tasks were tested for imbalance, namely standing, twisting, and walking, by the PD patient and the control. A neurologically normal adult was also tested as a negative control without any Parkinson pathology. The two subjects described above were carefully monitored and analyzed in terms of pitch and roll deviation before, during, and after the three motor tasks, and the postural stability was measured precisely.

2. METHODOLOGY

2.1 System Architecture

The Arduino device consisted of four stages of data collection: motion sensing, data acquisition, orientation calculation, and data analysis. The MPU6050 sensor transmitted the data of the standard coordinate axis (x, y, and z axes) to the Arduino using the I2C communication protocol, and the Arduino received the data and calculated the roll and pitch parameters. The values of the roll and pitch were then plotted and analyzed to assess imbalance on each participant.

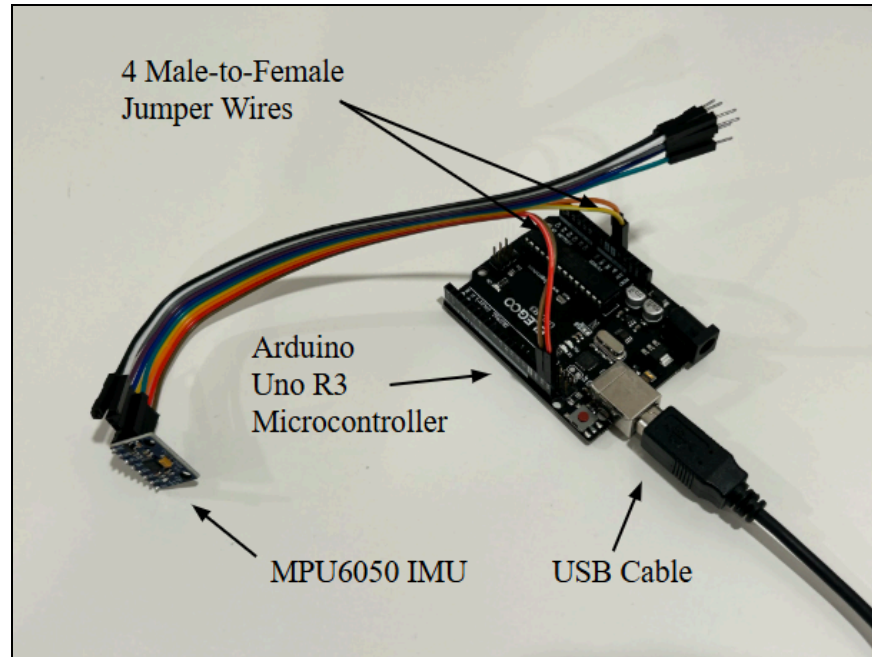


Figure 1: Diagram of Arduino Uno R3 Microcontroller

2.1.1 Arduino Uno R3 Board

The Arduino Uno R3 board was used for processing the MPU6050 sensor data. This device is portable and easily accessible, especially in clinical and community health environments where specialized motion analysis equipment is not available or limited (Salchow-Hömmen et al., 2022). The system is also laboratory independent, as it is designed based on low-cost embedded computing, thus increasing the accessibility and scalability of postural monitoring for clinicians and decreasing the cost of postural monitoring (Sica et al., 2024). This approach will provide more reliable data collection and, simultaneously, will meet the diagnostic sustainability objectives for underserved patient populations and point-of-care technology.

2.1.2 MPU6050 Inertial Measurement Unit (IMU)

After considering 3 other alternatives, the accelerometer (ADXL345), the IMU (BNO055), and the IMU (LSM6DS3), the MPU6050 IMU was selected as the sensing module. The ADXL345 is not capable enough to produce the rotational data required for this device; lacking an integrated gyroscope, the device is only able to measure the acceleration-based tilt, which causes large drift errors over time (Analog Devices, 2009). Although the BNO055 IMU has all the necessary functions, it is not a feasible option for the wearable device to be affordable in resource-constrained research settings (Bosch Sensortec, 2014). The BNO055 IMU can provide more accurate orientation estimates than the MPU6050, but this is not necessary to detect the amount of postural instability seen in Parkinson's disease. Unlike the MPU6050,

which offers fully flexible I2C address configuration and supports six-axis output (STMicroelectronics, 2017), the LSM6DS3 is not as flexible in terms of I2C address configuration. I2C address flexibility is the ability to configure the module communication interface that enables the development of accurate and precise sensor readings. The MPU6050 was the most economical and technically capable module for long-term inertial data collection due to the relatively straightforward wiring requirements and the fact that it had a combined accelerometer and gyroscope on a single chip (InvenSense, 2013).

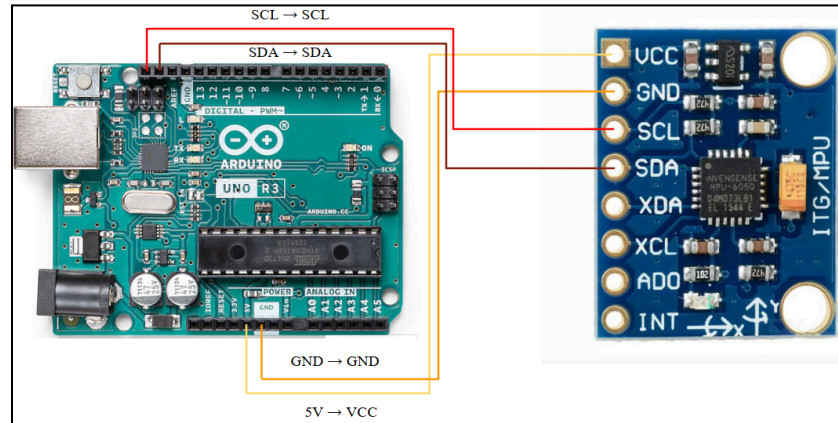


Figure 2: Circuit Diagram of Wearable Device

2.1.3 IMU Calibration

The device underwent a 30-second stationary warm-up followed by a 1,000-sample averaging routine to compute accelerometer and gyroscope zero offsets, which were subtracted from all subsequent readings. Raw accelerometer-derived angles were low-pass filtered ($\alpha = 0.08$) and fused with integrated gyroscope rate using an adaptive complementary filter (base weight $\alpha = 0.96$, dynamically adjusted by instantaneous gyroscope magnitude) to compute final pitch and roll. A background auto-recalibration routine continuously adjusted sensor offsets whenever the device was detected as stationary (gyroscope magnitude below $0.5^\circ/\text{s}$). Data was sampled and logged at 50 Hz (20 ms intervals). Calibration was performed independently for each participant via the full warm-up and offset procedure, and repeated between individual trials within a participant's session. The pin diagram of the used Arduino Uno R3 microcontroller is shown in figure 1. It specifies the colour and the connection of each wire.

2.1.4 Male-to-Female Jumper Wire Connections

The MPU6050 module was directly connected to the Arduino Uno R3 using male-to-female jumper wires. The four male-to-female jumper wires were soldered directly to the VCC, GND, SDA, and SCL pins of both components. This enhanced connection stability and portability, since a breadboard-based device would need extra wiring and a bigger module in general. Table 1 shows a description of what each connection between the sensor and the Arduino device means.

Table 1: Pin Connection Between Arduino Microcontroller and MPU6050

MPU6050 Pin	Arduino Uno Pin	Function
VCC	5V	Power Supply
GND	GND	Ground
SDA	SDA	Data Transfer
SCL	SCL	Clock Signal

2.1.5 USB Power Supply

A 12ft USB power cord was used to power the Arduino Uno R3, which meant that the participants were able to move around freely while the device was connected to a computer.

2.2 Arduino Integrated Development Environment (IDE)

The device configurability was decided on Arduino IDE, an open-source IDE. Consequently, tools like the serial monitor and data logging were used to facilitate data collection, making it much easier and efficient.

2.3 Shoulder Mounting Placement

The device was placed on the patient's right shoulder, and whole-body postural shifts were monitored without interfering with the movement being tested. This placement records postural deviation in both roll and pitch at 20 millisecond sampling rates, thus capturing the full spectrum of postural signals needed at a high temporal resolution and enhancing the sensitivity to detect subtle balance deficits (Caramia et al., 2019; Washabaugh et al., 2017). This site was chosen as it is a sensitive site for capturing the overall postural change across all three motor tasks, with the upper trunk being visibly shifted with lateral and forward-backward lean. Several other placements were considered and tested before arriving at this decision. The lower back was too far away from the center of mass to reliably capture lateral shifts of the trunk, leading to inconsistent readings during rotational tasks. The ankle had better gait mechanics data but was not suitable for standing and twisting tasks and had very limited sensitivity to whole-body lean. The sternum was also tested but was not able to capture lateral postural shifts to a considerable degree during the twisting task and was deemed less practical due to its discomfort during prolonged wear and its interference with upper body rotation. The shoulder was ultimately selected, as it has higher sensitivity to whole-body lean compared to the more distal ankle placement, allowing for the capture of both lateral and anterior-posterior postural deviation across all three motor tasks (Sica et al., 2024).

The wearable sensor was placed on the shoulder to record the motion of the trunk and upper body, which are related to postural instability and imbalance. The shoulder was chosen as a site for monitoring changes in body orientation and movement during standing and routine postural activity because it is a convenient

and non-invasive site. Shoulder-mounted sensing does not measure all components of gait and postural control directly, however. The recorded signals may be related to sensor orientation, individual body morphology, arm motion and compensatory arm motion. Thus, the results of the measurements obtained in this study should be viewed as movement-related rather than as a comprehensive assessment of whole-body balance.



Figure 3: Shoulder Placement on a Neurologically Healthy 48-year-old male (Participant 1) and a 77-year old Female with Parkinson's Disease (Participant 2)

2.4 Adhesive Mounting Tape

Adhesive tape was used to mount and secure the entire device onto the participant's right shoulder at a constant position in all trials.

2.5.1 Study Design:

The investigation was designed to be a preliminary proof of concept to assess the feasibility of a framework that could use wearable sensors to capture and analyze biomechanical parameters associated with movement. Approximately two minutes of each participant was monitored. This small sample size was chosen to perform an initial technical evaluation of the sensing and modelling workflow. This generated participant-level observations which were described in order to show the framework working, but no statistical comparisons were powered or clinical efficacy established.

Two participants were included in this study: a neurologically healthy 48-year-old male with no known neurological disorders and a 77-year-old female who had been diagnosed with Parkinson's disease in 2020. The Parkinson's patient was the PD participant, and the healthy participant was the control participant for comparison against Parkinsonian movement. Consent was taken from both of the participants prior to the experimental tests.

2.5.2 Standing Task

Participants stood slowly upright with their feet aligned with their shoulders while attempting to remain stationary. This task evaluated the stationary balance of the participants, as standing isolates postural stability (Schlachetzki et al., 2017). This task was repeated 3 times per participant, and the pitch and roll values reported in Figure 5 represent the mean across these 3 repeats.

2.5.3 Twisting Task

The participants started in a standing position and rotated their upper bodies to the left and right twice. This task evaluated rotational stability, as upper body rotation requires balance in a different way compared to the standing task (Caramia et al., 2019). This task was repeated 3 times per participant, and the pitch and roll values reported in Figure 6 represent the mean across these 3 repeats.

2.5.4 Walking Task

The participants walked a lap of a 20-meter path, which included both left and right turns. This task evaluated dynamic balance during motion, as walking is the most functionally demanding of the three tasks and is among the most commonly impaired movements in Parkinson's disease (Caramia et al., 2019; Schlachetzki et al., 2017). This task was repeated 3 times per participant, and the pitch and roll values reported in Figure 7 represent the mean across these 3 repeats.

2.6 OpenSim Musculoskeletal Modeling Software

OpenSim musculoskeletal modeling software, specifically the Optimal Jump model, was chosen for the biomechanical simulation after evaluating its compatibility, accuracy, and accessibility (Delp et al., 2007). The Optimal Jump model is a non-invasive computer simulation to model leg muscle movements when a human jumps. In order to model the control participant to the PD participant in this model, the model was tested with all muscles functioning (healthy model condition) and another model with three leg muscles being turned off (simulated PD condition). The vastus intermedius, gluteus maximus, and rectus femoris were the three leg muscles turned off in the model to mimic the PD participant, as those muscles have the most impact on Parkinson's patients when jumping (Stevens-Lapsley et al., 2012; Pongmala et al., 2024). These three muscles were selected due to their disproportionate weakness and activation deficit in Parkinson's disease patients, as reported in prior literature (Stevens-Lapsley et al., 2012; Pongmala et al., 2024). Since disabling these muscles entirely does not reproduce the graded weakness, rigidity,

bradykinesia, tremor, and altered coordination seen in real PD patients, this condition is best understood as a hypothetical impaired-muscle simulation representing one possible cause of reduced force output, rather than a patient-specific model of PD. The jumping task was used because of its established role in the Optimal Jump model, not because of a direct biomechanical link to the standing, twisting, and walking tasks used in the sensor portion of this study; the goal of the simulation was to illustrate a general muscle-force deficit pattern rather than to replicate the specific motor tasks tested experimentally. The OpenSim simulations were run independently of the sensor-derived pitch and roll data, as muscle disabling in the model was based on literature-reported Parkinsonian muscle deficits (Stevens-Lapsley et al., 2012; Pongmala et al., 2024) and not on the angular measurements recorded from the PD participant. The IMU and OpenSim components of this framework therefore provide two separate lines of evidence rather than a directly coupled pipeline, with the sensor quantifying observed postural imbalance and OpenSim illustrating a possible underlying muscle-force mechanism. Furthermore, since OpenSim simulation is iterative, it is an effective tool for repeated comparison between healthy and impaired muscle function (Delp et al., 2007). OpenSim's open-source availability and low computational requirements complement its use in resource-limited research settings (Delp et al., 2007). Figure 4 describes the formula for calculating the amount of force (in Newtons) created by each muscle in OpenSim.

$$F^M = F_0^M \left[a(t) f_{AL}(\tilde{l}^M) f_V(\dot{\tilde{l}}^M) + f_{PE}(\tilde{l}^M) \right]$$

$$F^T = F^M \cos \phi$$

Figure 4: Formula for Muscle Force (in Newtons) Calculation in Optimal Jump Model (Delp et al., 2007; Seth et al., 2011)

Term	Name	Definition
F^M	Muscle fiber force	The force produced by the muscle fibers themselves, before the force passes to the tendon, in newtons.
F_0^M	Maximum isometric force	Muscle's individual max strength without changing length, in Newtons.
$a(t)$	Activation, 0 to 1	Effort, on a scale of 0 to 1,

		where 0 represents a relaxed muscle and 1 is a fully activated muscle.
f_{AL}	Active force-length multiplier	How much force the muscle will produce based on its length.
f_v	Force-velocity	Effect of contraction velocity on force. Values less than 1 are found during contraction and greater than 1 during stretching. Isometric contraction has a value of ≈ 1 .
f_{PE}	Passive force-length multiplier	Resistance against the muscle being stretched. It is almost 0 at rest and increases exponentially as the muscle stretches.
τ^M	Normalized fiber length	How far away is the muscle fiber length from optimal conditions (ex: 1.1 is 10% longer, and 0.9 is 10% shorter).
F^T	Tendon force, transmitted to the skeleton	Force transmitted through the tendon to the skeleton in Newtons.
ϕ	Pennation angle	The angle at which the muscle fibers are attached to the tendons.

Table 2: Description of Variables Used in Calculation of Muscle Force in Newtons

3. RESULTS AND DISCUSSION

A single shoulder-mounted sensor is a practical and minimally intrusive approach but also has limitations. Lower-limb kinematics, foot placement, and other biomechanical variables that are important for balance and gait instability may not be measured at a single sensing location. Further research is thus warranted to determine if further sensors placed on the trunk, pelvis and lower limbs would enhance the ability to characterise postural and gait-related abnormalities.

3.1 Standing Task

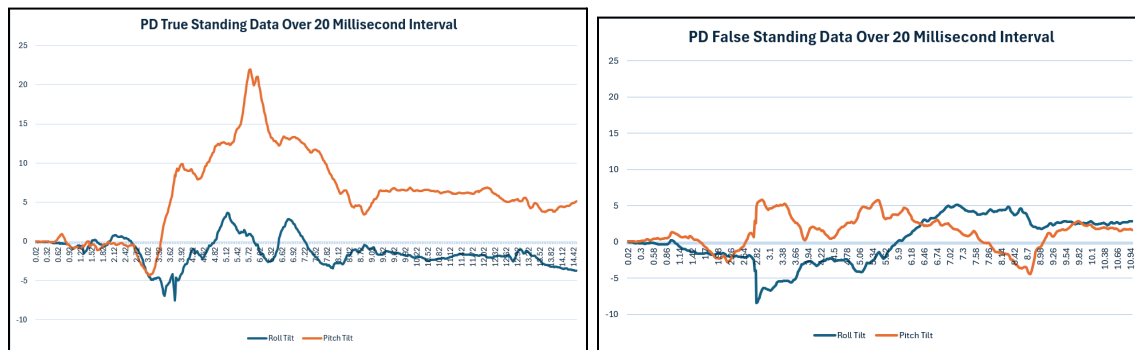


Figure 5A and 5B: Graphs Comparing Participant's Average Pitch and Roll Tilt for PD Participant in Figure 5A and Control Participant in 5B in Standing Task over 3 Repeated Trials. The graphs show angular measurements of pitch and roll during a standing test for the healthy control and PD participant.

The graph for the PD participant shows a large forward pitch displacement while attempting to stand upright, whereas the roll axis shows comparatively modest oscillations. The healthy control participant was, however, relatively stable with minor fluctuations throughout the test, and this shows good postural control when standing.

The PD participant experienced a large forward pitch imbalance during the standing trial when attempting to rise up, with the participant reaching a maximum forward pitch of approximately 22 degrees and then slowly decreasing, with roll values ranging from -7 degrees to +3 degrees. This data shows that the PD participant needed an extended amount of time in order to complete postural realignment, where the participant's pitch angle stayed consistently at around 5-6 degrees. However, the control participant showed pitch values that were mostly within ± 6 degrees, suggesting a more controlled response of forward-leaning. Interestingly, the healthy control participant also exhibited a small roll deviation of ~ -8 degrees around 2.8 seconds before recovering. This indicates that the main postural difference between participants in the standing task was in the pitch axis (forward lean), with the PD participant having a significantly larger and longer displacement. The time to complete the trials for each participant was 14.42 s for the PD participant and 10.94 s for the control participant.

3.2 Twisting Task

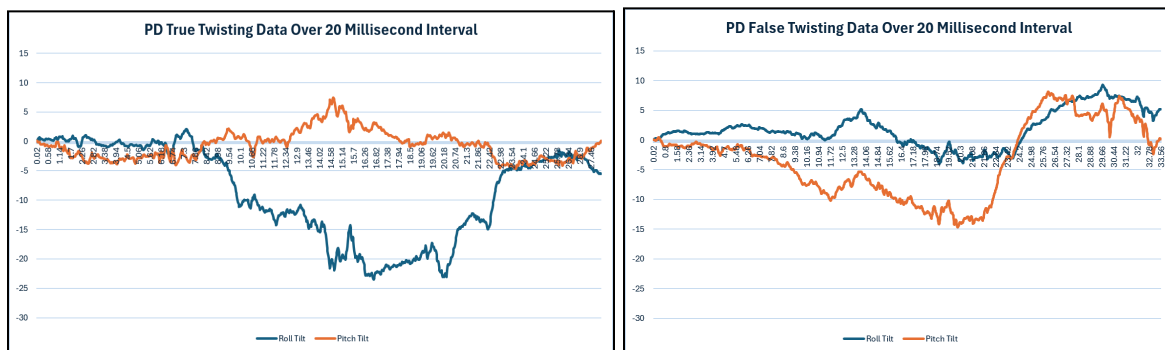


Figure 6A and 6B: Graphs Comparing Participant's Average Pitch and Roll Tilt for PD Participant in Figure 6A and Control Participant in 6B in Twisting Task over 3 Repeated Trials. These plots show the comparison of roll and tilt of a twisting motion for the PD participant and healthy control participant. The PD participant showed a marked and sustained roll to the right during upper-body rotation, consistent with reduced rotational control. The healthy control shows coordinated roll and tilt patterns, which are similar to the intended twisting motion, suggesting stable and symmetric motor control.

The PD participant exhibited a large roll imbalance to the right when attempting to rotate the upper body, with a maximum roll of about 23-25 degrees for a long period of the trial and a relatively small pitch of about 7 degrees throughout the trial. This data shows that the PD participant took a longer time to re-stabilize after rotation, and during this time the participant's roll angle was high for a large percentage of the trial before the patient began to recover. The control participant, on the other hand, had a more controlled rotational response with roll values near 0 degrees throughout the trial, rising to approximately 7 to 9 degrees towards the end of the trial. Of particular interest, the healthy control participant also exhibited a pitch tilt that decreased to around -15 degrees during the rotational phase and then increased back to around 7 to 8 degrees. This means that the primary difference between the participants in the twisting task was the roll axis (sideways lean), which was significantly more and longer displaced in the PD participant. In terms of how long it took to complete the task, the PD participant took 27.46 seconds, whereas the control participant took 33.56 seconds.

3.3 Walking Task

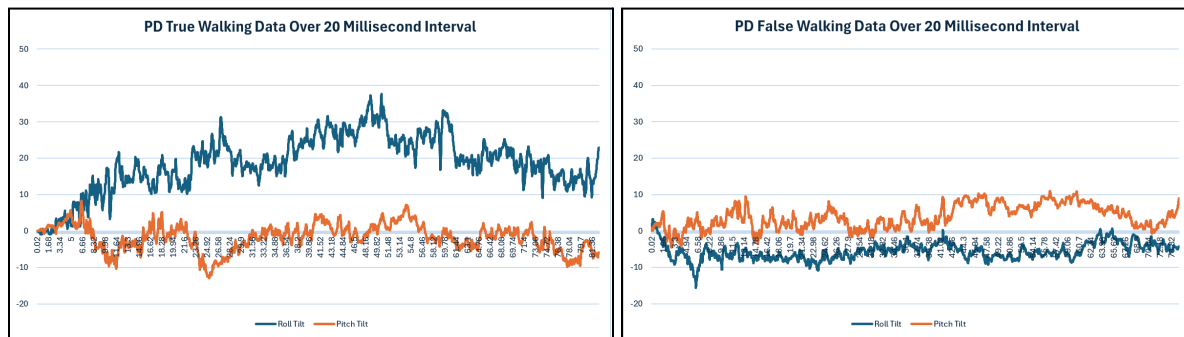


Figure 7A and 7B: Graphs Comparing Participant's Average Pitch and Roll Tilt for PD Participant in Figure 7A and Control Participant in 7B in Walking Task over 3 Repeated Trials. These plots display the pitch and roll data for the PD participant and the control participant while walking. The PD participant shows progressively increasing lateral (roll) imbalance over time, with pitch remaining comparatively stable. The healthy control participant was again relatively stable with small variations throughout the test, indicating normal postural control ability during walking.

The PD participant had a large and progressively increasing roll imbalance to the left (which increased rapidly during the first 0-25 seconds of the walking trial, up to approximately 37 degrees, and remained elevated throughout the rest of the walking trial), and pitch values were between approximately -10 and 7 degrees. This data shows that the PD participant was unable to correct their postural lean during the walking task, and the patient's roll angle was elevated at about 15-35 degrees for most of the trial. The healthy control participant, however, remained mostly between -10 to 0 degrees of roll during the trial, indicating a more controlled gait pattern with no directional drift. Notably, the control participant also had a short excursion to the right of about -17 degrees early in the trial, before returning to the -10 to 0 degree range for the rest of the trial. However, this data point could have resulted from sensor error. This suggests that the primary difference between the walking task groups was in the roll axis (sideways lean), with the PD participant having a significantly greater and more consistent roll axis displacement. The duration of the trials was around 81.36 seconds for the PD participant and 73.82 seconds for the control participant.

Table 3: Short Summary of Each Task. Across all trials, the PD participant demonstrated larger angular deviations, greater variability, and slower stabilization compared to the healthy control participant. The control participant showed smaller deviations and more even movement patterns across roll and pitch axes during standing, twisting, and walking tasks.

Task	Measured Metric	PD Participant	Control Participant
Standing	Pitch tilt magnitude	Large forward pitch displacement, peaking at $\sim 22^\circ$	Smaller pitch changes, generally within $\pm 6^\circ$
	Roll tilt variability	High variability with repeated oscillations ($= -7^\circ$ to $+3^\circ$)	Lower variability and fewer oscillations
	Postural stabilization	Delayed stabilization after standing	Faster return to neutral posture
Twisting	Roll tilt during rotation	Pronounced and sustained rightward roll ($= -23^\circ$ to -25°)	Moderate roll changes that reversed toward baseline
	Pitch/roll coordination	Poor coordination between pitch and roll during twist	Complementary pitch and roll patterns
	Recovery after peak displacement	Slower recovery to baseline orientation	Faster recovery and realignment
Walking	Roll tilt trend over time	Gradual directional drift (leftward lean up to $\sim 25^\circ$)	No sustained drift; roll remained near baseline
	Pitch tilt consistency	Irregular oscillations with slight forward bias	More consistent pitch with short-duration fluctuations
	Gait stability indicators	Increasing imbalance over time	Stable gait with frequent small corrections

3.4 OpenSim Modeling

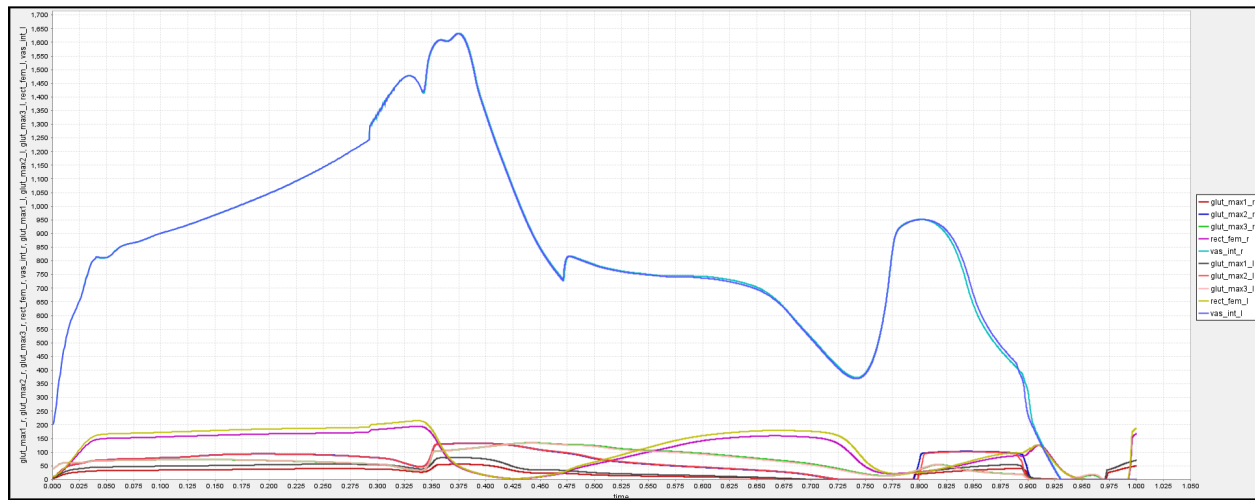


Figure 8: Simulated PD Condition Musculoskeletal Graph

The muscle force for a simulated PD condition is shown in the graph in OpenSim. The peak muscle force is decreased and less synchronized in the leg muscles during the jump phase, followed by a rest period of 0.6-1.0 s during which muscle forces stabilize.



Figure 9: Musculoskeletal Graph of a Healthy Model Condition

The graph shows the muscle force of an OpenSim healthy model condition. During the jump, muscles produce higher and more coordinated peak forces, followed by a rest period of 0.6-1.0s.

During the jumping task, there were clear differences in muscle activation and force production between the simulated PD condition and the healthy model condition in the OpenSim simulations. During the simulated PD condition, peak force production in the gluteus maximus, rectus femoris, and vastus intermedius was lower, with peak vastus intermedius force reaching approximately 1,630 N in the

simulated PD condition compared to approximately 2,300 N in the healthy model condition, a reduction of roughly 29%; peak gluteus maximus and rectus femoris forces were comparable between conditions (~900-950 N each). The force curves of the muscles exhibited a decrease in maximum force and a more gradual increase, indicating a decrease and delay in force. This decrease was most noticeable during the jump's takeoff, when a series of coordinated activations are needed to create lift in the vertical direction. The healthy model condition, on the other hand, had higher and more distinct peaks in muscle force, particularly in the vastus intermedius, which reached its peak faster and at a higher magnitude than in the simulated PD condition. In the healthy model condition, the force was quickly generated at the beginning of the movement and maintained for a long time, with a gradual decrease in the force, indicating efficient neuromuscular coordination. Furthermore, muscle activation during the healthy model condition was more coordinated, with the quadriceps and hip extensors having peak forces within a short time. Further analysis revealed that the simulated PD condition had force plateaus that lasted longer and transitions between phases of the movement that were irregular. The secondary peak or incomplete force recovery after initial activation was observed in several muscles. These irregularities were not observed in the healthy model condition, and the force output was smoother and more continuous.

CONCLUSION

This study aimed to understand the feasibility of quantifying the imbalance characteristics between the control participant and the PD participant by using a shoulder-mounted MPU6050 sensor and the OpenSim musculoskeletal modeling. In all trials, the PD participant had greater pitch and roll deviations than the control participant. The PD participant also took longer to complete the standing and walking tasks. However, the PD participant completed the twisting task faster than the control participant because the trial was terminated early due to instability, not because of better performance, so task duration should be interpreted alongside whether the task was actually completed rather than as a standalone measure of performance. Altered leg muscle forces were also seen in the simulated PD condition compared to the healthy model condition. While the small sample size and the reliability of the Arduino sensor are limitations, this study demonstrated that a small wearable device could detect and analyze quantitative movement characteristics in Parkinson's disease. More studies with better sensors and more participants are required before the system can be used for clinical monitoring.

A major limitation of this study is the two-participant sample size. The comparison between the participants is descriptive only and cannot be extended to the general population of patients with Parkinson's disease and should not lead to statistical generalization or draw conclusions about the effectiveness of the proposed framework for all patients with Parkinson's disease. Furthermore, because of the limited monitoring time, variability over longer times and in different levels of movement can not be assessed. The results should therefore be considered pre-clinical, and not clinical. Only one person with PD and one healthy control participant were tested. Although differences in pitch, roll, task duration and muscle-force patterns were found, these findings cannot be representative of the over 10 million people worldwide who suffer from Parkinson's disease (World Health Organization, 2023). The symptoms of

Parkinson's disease may differ significantly from one person to another depending on the stage of the disease, medications, age, and level of motor impairment. The study would need to be repeated with a larger number of participants to see if the movement patterns found in this study are consistent in a wider range of Parkinson's patients.

In addition, the effectiveness of the system is technically limited. The Arduino-based MPU6050 sensor was a low-cost way to gather motion data, but it might not be as consistent as newer wearable clinical motion sensors. The pitch and roll values recorded may have been influenced by sensor drift, minor changes in sensor placement on the shoulder, body orientation, and movement artifacts (Prisco et al., 2024). One sensor also meant that the system was not able to measure coordination between the trunk, hips, knees, ankles, and feet. The data gathered may therefore not represent all of the movement characteristics of Parkinson's disease. Additionally, while averaging across the 3 repeated trials improved the reliability of the reported values compared to a single measurement, standardized metrics such as mean absolute deviation, time outside a defined stability threshold, and recovery time were not calculated in this study and are left for future work.

The restrictions found provide several avenues for future research and development. Future studies should include a larger and more diverse population, including people with varying stages of Parkinson's disease. If the trials were repeated over several days, it would be possible to see if the sensor is able to record consistent movement data over time. Future versions might feature multiple sensors on the lower limbs and trunk, rather than one on the shoulder. This would enable the system to measure stride timing, gait symmetry, turning behavior, trunk sway, and joint coordination more comprehensively. Better filtering, calibration methods, and OpenSim models for individual participants would also help minimize data error and increase the accuracy of the musculoskeletal simulations.

The prototype can also be expanded to become a more user-friendly movement monitoring system. The current model was put together, programmed, and tested for basic functionality in about an hour, demonstrating that low-cost components can be used to detect measurable differences between a Parkinson's participant and the control participant. The proposed framework might offer a relatively simple and accessible way to monitor movement, as it is based on wearable sensors and computational biomechanical analysis. In the current proof-of-concept study, however, there was no formal assessment of the affordability or clinical accessibility. The cost of the system was not directly compared to other clinical evaluation systems or commercially available wearable systems. Thus, the results of the present study should not be interpreted as proof of clinical cost-effectiveness or affordability. Further studies will require a detailed economic and usability evaluation.

The results of this study should be viewed as preliminary, as it was a proof-of-concept evaluation with only two participants. The small number of subjects does not allow for statistical generalisations to the broader Parkinson's population and to people with varying stages and levels of motor dysfunction. Furthermore, there are individual differences in body morphology, movement patterns, balance strategy and sensor positioning that can affect the recorded measurements.

The present study is therefore not a clinical validation of the proposed monitoring framework but rather a demonstration of the technical feasibility of the proposed framework. Future studies should include a much larger and more diverse sample with patients across the spectrum of Parkinson's disease and healthy controls. Multiple measurements should also be repeated over multiple sessions to assess intra- and inter-subject variability, measurement reliability, and robustness to sensor placement changes. The biomechanical parameters derived from the wearable system would also need to be compared with existing clinical tools used to assess balance and gait to establish the clinical significance of the wearable system.

The use of more sensor sites and/or biomechanical parameters should also be evaluated for its sensitivity and reliability in assessing imbalance. These studies would have to be done prior to the framework being used in clinical decisions or for diagnosis.

Finally, future studies could investigate if repeated sensor measurements can detect changes in motor function prior to when they are apparent during routine clinical assessment. The device is not designed to make a diagnosis of Parkinson's, but it may be able to measure movement data that the clinician can use to track changes between visits. This system may be used to track movement impairment associated with Parkinson's, with better reliability and a larger number of participants and wearable sensors, making it a more useful tool for clinical intervention earlier in the disease.

REFERENCES

1. Analog Devices. (2009). *ADXL345: 3-axis, ± 2 g/ ± 4 g/ ± 8 g/ ± 16 g digital accelerometer* [Data sheet]. <https://www.analog.com/media/en/technical-documentation/data-sheets/adxl345.pdf>
2. Bloem, B. R., Hausdorff, J. M., Visser, J. E., & Giladi, N. (2004). Falls and freezing of gait in Parkinson's disease: A review of two interconnected, episodic phenomena. *Movement Disorders*, 19(8), 871–884. <https://doi.org/10.1002/mds.20115>
3. Bosch Sensortec. (2014). *BNO055: Intelligent 9-axis absolute orientation sensor* (Rev. 1.2) [Data sheet]. <https://www.bosch-sensortec.com/media/boschsensortec/downloads/datasheets/bst-bno055-ds000.pdf>
4. Caramia, C., De Marchis, C., & Schmid, M. (2019). Optimizing the scale of a wavelet-based method for the detection of gait events from a waist-mounted accelerometer under different walking speeds. *Sensors*, 19(8), 1869. <https://doi.org/10.3390/s19081869>
5. Chu, Y., Hirst, W. D., Federoff, H. J., Harms, A. S., Stoessl, A. J., & Kordower, J. H. (2024). Nigrostriatal tau pathology in parkinsonism and Parkinson's disease. *Brain*, 147(2), 444–457. <https://doi.org/10.1093/brain/awad388>

6. De Groote, F., & Falisse, A. (2021). Perspective on musculoskeletal modelling and predictive simulations of human movement to assess the neuromechanics of gait. *Proceedings of the Royal Society B: Biological Sciences*, 288(1946), 20202432. <https://doi.org/10.1098/rspb.2020.2432>
7. Delp, S. L., Anderson, F. C., Arnold, A. S., Loan, P., Habib, A., John, C. T., Guendelman, E., & Thelen, D. G. (2007). OpenSim: Open-source software to create and analyze dynamic simulations of movement. *IEEE Transactions on Biomedical Engineering*, 54(11), 1940–1950. <https://doi.org/10.1109/TBME.2007.901024>
8. di Bello, B. M., Casella, A., Aydin, M., Lucia, S., Di Russo, F., & Pitzalis, S. (2024). Electrophysiological indexes of the cognitive-motor trade-off associated with motor response complexity in a cognitive task. *NeuroImage*, 303, 120931. <https://doi.org/10.1016/j.neuroimage.2024.120931>
9. Dong, H., Chen, Z.-K., Guo, H., Yuan, X.-S., Liu, C.-W., Qu, W.-M., & Huang, Z.-L. (2022). Striatal neurons expressing dopamine D1 receptor promote wakefulness in mice. *Current Biology*, 32(3), 600–613.e4. <https://doi.org/10.1016/j.cub.2021.12.026>
10. InvenSense. (2013). *MPU-6000 and MPU-6050 product specification* (Rev. 3.4) [Data sheet]. https://www.cdiweb.com/datasheets/invensense/mpu-6050_datasheet_v3%204.pdf
11. Kwon, D. K., Kwatra, M., Wang, J., & Ko, H. S. (2022). Levodopa-induced dyskinesia in Parkinson's disease: Pathogenesis and emerging treatment strategies. *Cells*, 11(23), 3736. <https://doi.org/10.3390/cells11233736>
12. Michael J. Fox Foundation for Parkinson's Research. (2026, March 26). New report finds Parkinson's disease cost patients, families and the federal government \$82.2 billion in 2024. <https://www.michaeljfox.org/news/new-report-finds-parkinsons-disease-cost-patients-families-and-federal-government-822-billion>
13. Parkinson's Foundation. (2024). Statistics. <https://www.parkinson.org/understanding-parkinsons/statistics>
14. Pongmala, C., Stonsaovapak, C., Luker, A., Griggs, A., van Emde Boas, M., Haus, J. M., & Bohnen, N. I. (2024). Association of specific leg muscle strength and motor features in Parkinson's disease. *Parkinson's Disease*, 2024, 5580870. <https://doi.org/10.1155/2024/5580870>
15. Prisco, G., Pirozzi, M. A., Santone, A., Esposito, F., Cesarelli, M., Amato, F., & Donisi, L. (2024). Validity of wearable inertial sensors for gait analysis: A systematic review. *Diagnostics*, 15(1), 36. <https://doi.org/10.3390/diagnostics15010036>
16. Salchow-Hömmen, C., Skrobot, M., Jochner, M. C. E., Schauer, T., Kühn, A. A., & Wenger, N. (2022). Review—Emerging portable technologies for gait analysis in neurological disorders. *Frontiers in Human Neuroscience*, 16, 768575. <https://doi.org/10.3389/fnhum.2022.768575>
17. Schlachetzki, J. C. M., Barth, J., Marxreiter, F., Gossler, J., Kohl, Z., Reinfelder, S., Gassner, H., Aminian, K., Eskofier, B. M., Winkler, J., & Klucken, J. (2017). Wearable sensors objectively measure gait parameters in Parkinson's disease. *PLOS ONE*, 12(10), e0183989. <https://doi.org/10.1371/journal.pone.0183989>
18. Seth, A., Sherman, M., Reinbolt, J. A., & Delp, S. L. (2011). OpenSim: A musculoskeletal modeling and simulation framework for in silico investigations and exchange. *Procedia IUTAM*, 2, 212–232. <https://doi.org/10.1016/j.piutam.2011.04.021>

19. Sica, M., Varnosfaderani, O. T., Crowe, C., Kenny, L., Bocchino, A., O'Flynn, B., Mueller, D., Tedesco, S., Timmons, S., & Barton, J. (2024). Design of a multi-sensors wearable system for continuous home monitoring of people with Parkinson's. *IEEE Access*, 12, 38436. <https://doi.org/10.1109/ACCESS.2024.3375871>
20. Stevens-Lapsley, J., Kluger, B. M., & Schenkman, M. (2012). Quadriceps muscle weakness, activation deficits, and fatigue with Parkinson disease. *Neurorehabilitation and Neural Repair*, 26(5), 533–541. <https://doi.org/10.1177/1545968311425925>
21. STMicroelectronics. (2017). *LSM6DS3TR-C: Always-on 3D accelerometer and 3D gyroscope* [Data sheet]. <https://www.st.com/resource/en/datasheet/lsm6ds3tr-c.pdf>
22. Washabaugh, E. P., Kalyanaraman, T., Adamczyk, P. G., Claflin, E. S., & Krishnan, C. (2017). Validity and repeatability of inertial measurement units for measuring gait parameters. *Gait & Posture*, 55, 87–93. <https://doi.org/10.1016/j.gaitpost.2017.04.013>
23. World Health Organization. (2023). *Parkinson disease* [Fact sheet]. <https://www.who.int/news-room/fact-sheets/detail/parkinson-disease>