Parkinsonian Gait Detection Using iPad LiDAR and Pose Estimation

Introduction

Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects over 10 million people worldwide, making it the second most common age-related neurodegenerative condition in North America [1]. Despite its prevalence, the current diagnostic process for PD remains primarily clinical and subjective. Diagnosis is typically based on the visual assessment of motor symptoms by neurologists, including tremors, bradykinesia, rigidity, and postural instability [2]. This observational method often results in delayed or inaccurate diagnoses, particularly during the early stages of the disease when symptoms may be subtle or inconsistent.

There is a growing need for accessible, objective, and non-invasive tools to support early detection and monitoring of Parkinson's. Gait abnormalities are among the earliest motor symptoms of PD and present a strong opportunity for automated analysis. Parkinsonian gait, as it is commonly known, is characterized by a range of distinct features, including reduced stride length, asymmetrical arm swing, and decreased joint range of motion. These movement irregularities often serve as early visible indicators of PD progression [3].

We propose a novel, low-cost system that combines LiDAR (Light Detection and Ranging) data from consumer-grade Apple devices (e.g. iPad Pro) with a vision-based human pose estimation model to extract 3D joint trajectories and gait features that will serve as a more accessible and objective PD detection pipeline. Google's MediaPipe pose estimation model provides a lightweight and efficient framework for tracking major body landmarks, including the elbows, hips, knees, shoulders, wrists, and ankles. By aligning pose landmarks with LiDAR depth data, our pipeline enables accurate reconstruction of 3D motion without requiring wearable sensors or specialized motion capture systems. This fusion of affordable hardware and real-time computer vision has the potential to enable scalable, at-home screening and monitoring for Parkinson's disease.

Related Work

Parkinsonian Gait Analysis with Wearable Technology

Gait analysis has long been used to aid in the detection of Parkinson's disease (PD), as early motor symptoms often include changes in stride length, gait speed, arm swing, and postural stability. Numerous studies have demonstrated the diagnostic value of these gait parameters in identifying early signs of PD [4] [5] [6]. Traditional approaches often rely on wearable devices such as inertial measurement units (IMUs), accelerometers, or gyroscopes to monitor gait dynamics [7]. As such, they are not well suited for continuous, large-scale, or at-home screening. Our work addresses these limitations by proposing a non-invasive and low-cost alternative for automated gait assessment using consumer devices.

Gait Analysis with Pose Estimation

Recent advances in computer vision have enabled markerless motion capture using pose estimation frameworks such as OpenPose and MediaPipe. These models can extract 2D joint locations from RGB video, enabling estimation of joint trajectories and limb movements without physical sensors. MediaPipe, in particular, is a lightweight and open-source model developed by Google that operates in real time on mobile devices, making it an attractive solution for at-home gait analysis [8]. Prior work has shown that joint trajectory features derived from pose estimation can help distinguish between healthy individuals and those with neurodegenerative disorders [9]. However, purely 2D approaches lack depth information and may struggle with occlusions or camera angle dependencies. Some systems attempt to overcome this by using multiple camera views, but such setups are impractical for everyday use. Our approach integrates pose estimation with LiDAR-based depth data to enhance the accuracy and robustness of gait analysis in uncontrolled settings.

LiDAR-based Gait Analysis

LiDAR technology has been increasingly explored for its potential in capturing accurate 3D motion data. Several studies have demonstrated the effectiveness of LiDAR-based systems in gait tracking and classification, including for Parkinson’s detection [10] [11]. These systems, however, often rely on high-end LiDAR sensors that are expensive and not widely available. In contrast, we leverage the LiDAR capabilities of commercially available Apple devices (iPhone 12 Pro or later and/or iPad Pro), which offer real-time depth sensing in a compact and affordable manner. By aligning this LiDAR depth data with MediaPipe pose landmarks, our system captures accurate 3D joint trajectories and can extract features indicative of Parkinsonian gait. This is one of the first approaches to combine consumer-grade LiDAR with pose estimation for Parkinson’s screening, enabling accessible and scalable home-based monitoring.

Methods

Experimental Setup

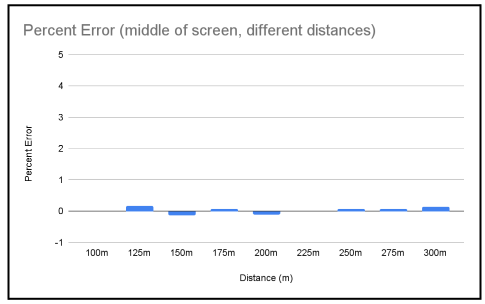
LiDAR recordings were captured using the Stray Scanner app on an iPad Pro M4. The app provides the necessary camera intrinsics, RGB video, depth maps, and depth confidence data. Videos were recorded at 60 frames per second at the iPad's maximum LiDAR resolution of 192×256 pixels. Subjects were seated approximately five meters from the camera, which was mounted on a tripod. The room was well-lit with no background motion. At the start of each recording, the subject was instructed to stand up and walk straight toward the camera. Recording was stopped once the subject exited the camera’s field of view.

Subjects were healthy volunteers who performed both a normal walk and a simulated Parkinsonian gait by mimicking symptoms such as reduced stride length, gait freezing, and slower walking speed. Each subject completed two walking trials. The dataset includes 5 subjects (3 male, 2 female) and a total of 10 videos.

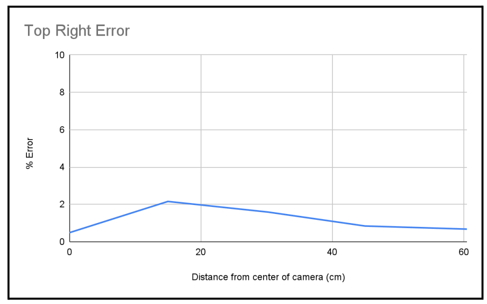
LiDAR Testing

To validate the iPad's LiDAR accuracy, we conducted a series of calibration tests across various spatial and environmental conditions.

1) Camera Center Testing: The LiDAR sensor was positioned 1 meter from a flat surface. At each 0.25 m increment (up to 3 m), we recorded the depth at the image center and compared it to the real-world measured distance. Across all distances, the error was under 0.25%, confirming high accuracy near the camera center.



2) Euclidean Distance Testing: We marked fixed points on a whiteboard corresponding to known positions in the RGB image and matched these with pixels in the depth map. Percent error across all points was below 3%, indicating consistent depth accuracy across the image frame.



3) Light vs Dark Test: Images were taken under varied lighting conditions. Depth values showed less than 0.5% variation, confirming that lighting and shadows have negligible impact on LiDAR accuracy.

Table 1: Light vs Dark % Error

Dark	Light	% error
96.5	96.3	0.207253886
92.9	92.8	0.1076426265
98.3	98.3	0
95.6	96	0.4184100418
78.8	78.9	0.1269035533

4) Color Test: Colored paper (dark blue, bright red) was placed on a whiteboard to test whether color affected depth measurements. Across all test points, differences between the colored and control (white) surfaces were under 1%, except for one outlier. Thus, surface color had minimal influence on LiDAR depth data.

Table 2: Color Test

	Blue (cm)	Red (cm)	White (cm)	% Diff Blue	% Diff Red
Middle	51.3	51.5	51.6	-0.5813953488	-0.1937984496
Left	57	57	57.2	-0.3496503497	-0.3496503497
Right	54.6	55.6	54.9	-0.5464480874	1.275045537
Top	52.9	53.1	53.2	-0.5639097744	-0.1879699248
Bottom	53.4	53.6	53.6	-0.3731343284	0

Data Processing and Analysis Pipeline

The MediaPipe framework identifies 33 anatomical landmarks per frame. For gait analysis, we focused on 12 key points, namely the left and right ankles, knees, hips, shoulders, elbows, and wrists. Each landmark has a unique pixel coordinate which we map to the LiDAR data from each frame, providing landmarks with z-axis depth values in meters.

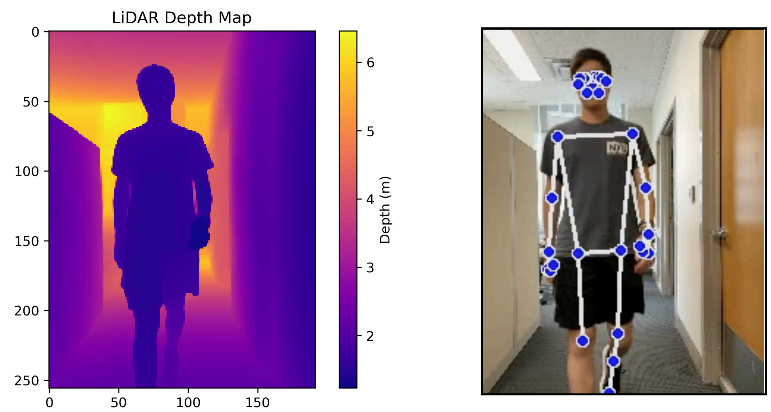


Fig. 1 & 2: LiDAR depth map with corresponding MediaPipe landmark map

By using the depth values of key landmarks we can extract the 3D coordinates of the targeted joints and calculate the angles they form relative to one another. To obtain the x and y locations of each joint relative to the center of the camera, we utilize the camera intrinsic data along with the depth data in meters, plugging them into the back-projection equations for a pinhole camera model:

$x = (u - cx) * d / fx$
$y = (v - cy) * d / fy,$

where (fx, fy) is the camera focal length components, (cx, cy) is the center pixel coordinate of the camera, (u,v) is the target pixel coordinate, and d is the depth in meters.

Having determined the 3D location of each pixel in the video, we are able construct 3D point cloud visualizations of the walking videos, and also calculate gait parameters such as knee, elbow, and hip angle. To calculate these angles, we utilize the cosine similarity formula.

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum\limits_{i=1}^{n} A_i B_i}{\sqrt{\sum\limits_{i=1}^{n} A_i^2} \sqrt{\sum\limits_{i=1}^{n} B_i^2}}$$

For example, in calculating the hip angle, we take the hip point as the pivot and identify a vector from the hip to the shoulder (A) and one from the hip to the knee (B). We then plug these into the cosine similarity formula which gives us the hip angle at each frame of the video.

Plotting the depth (z-axis distance) along with the angles of these joints over time as the subject walks towards the camera, we gain insight into gait patterns which can be used to determine abnormal gait. Some key characteristics of gait reflected in the graphs are the speed of the subject's gait, freezing or hesitation, range of motion, and gait rhythm.

Detrending

After mapping the pose landmarks to corresponding LiDAR depth measurements, we applied a polynomial detrending algorithm to the depth vs time signals. This process removes overall trends in the data – such as gradual forward movement – allowing for clearer visualization of cyclical gait patterns like walking, as demonstrated in Figures 6 and 7.

By analyzing the detrended signals, we can more reliably identify key gait characteristics, including asymmetry between left and right sides, step frequency, and the amplitude of joint oscillations. These features are critical for distinguishing normal gait from Parkinsonian gait, which is often marked by irregular rhythms and uneven leg movements.

Results

The goal of the experiment was to extract, analyze, and compare depth and joint angle data from LiDAR recordings of a subject performing a sit-to-stand transition and walking toward the camera with normal and Parkinsonian gait. Using the iPad Pro’s LiDAR sensor and the MediaPipe pose estimation model, we computed time series data for key joint angles (e.g., knee, hip, elbow) and their depth (z-axis) positions.

The following results include temporal profiles of both joint angles and depth trajectories. We also report observations of gait features characteristic of Parkinsonian movement, including reduced joint amplitude, irregular timing, and limited range of motion.

Joint Depth vs Time

Figure 3 displays the depth of the left knee joint over time, comparing a normal walk (blue line) with a simulated Parkinsonian gait (red line) from the same participant. The x-axis represents time in seconds, and the y-axis represents depth (distance from the iPad camera) in meters.

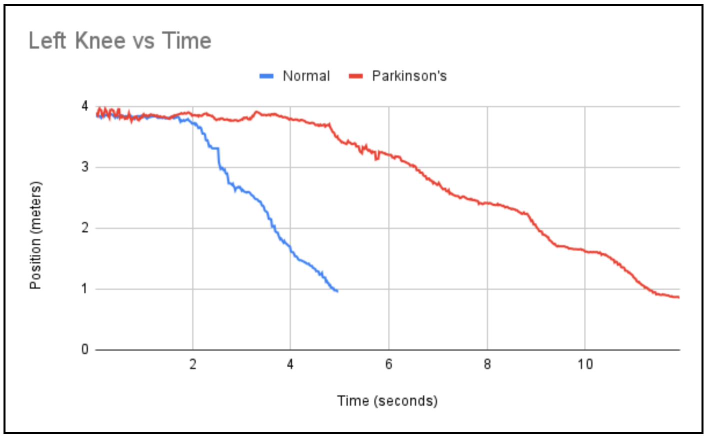


Fig. 3: Normal vs Parkinsonian left knee position over time

This graph illustrates clear differences between the two gait patterns. The normal walk demonstrates quicker, more dynamic motion with greater oscillation between steps. In contrast, the Parkinsonian gait is delayed and less consistent, characterized by a slower walking pace and smaller overall depth changes, indicative of reduced stride length. The hesitation observed at the start corresponds to difficulty initiating movement, a common Parkinson's symptom. These differences suggest that depth trajectories of key joints can serve as quantifiable markers for motor impairment in Parkinson's disease.

Joint Angle vs Time

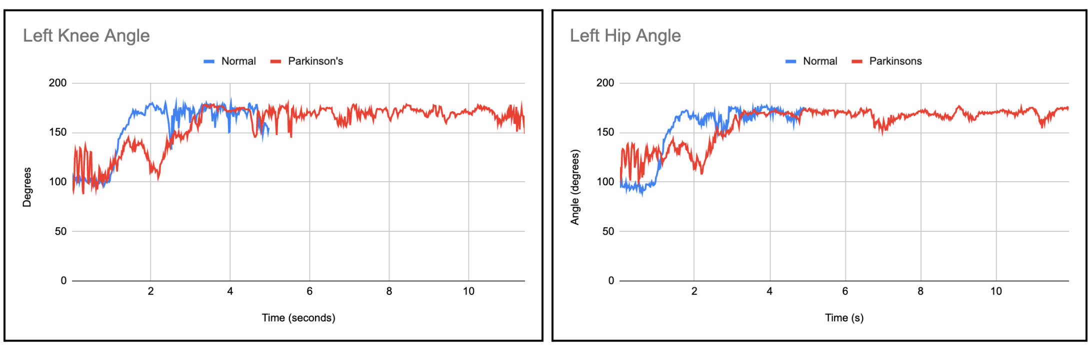


Fig. 4 & 5: Normal vs Parkinsonian left knee angle and left hip angle over time

Figures 4 and 5 display the left knee and left hip angles plotted over time. Initial lower angles (approximately 100–130 degrees) correspond to the subject sitting, with knees and hips flexed. As the subject stands, these angles increase toward 180 degrees.

Subjects simulating Parkinsonian gait exhibited prolonged difficulty standing, as reflected by their knee and hip angles taking around twice as long to reach their peak on average. Moreover, episodes of freezing of gait are visible when the joint angle momentarily decreases or plateaus before completing the standing motion.

Detrended Comparison

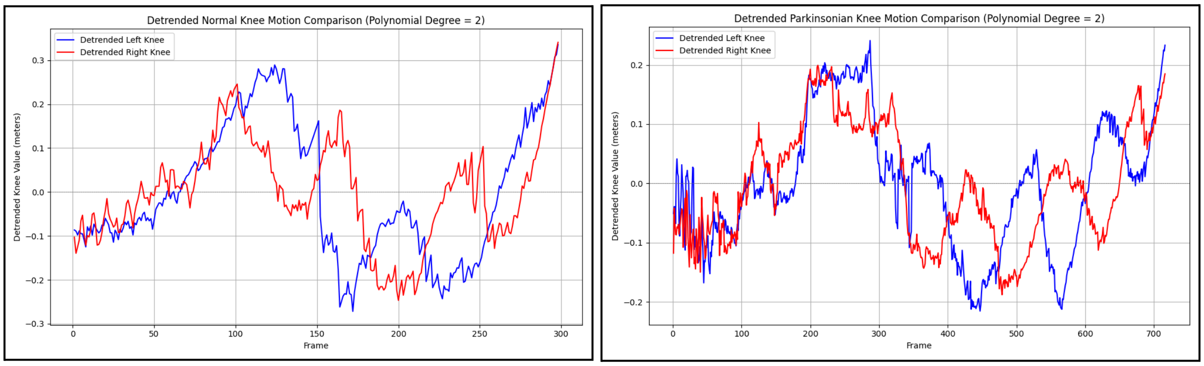


Fig. 6 & 7 Normal left and right knee detrended and Parkinsonian left and right knee detrended over time

Figures 6 and 7 display the detrended depth vs time graph of the left and right knee side by side for both normal walking (figure 6) and a subject simulating Parkinsonian gait (figure 7). The data from both knees are aligned to visualize bilateral leg movement.

In the normal gait, the knee motions display rhythmic, alternating peaks and troughs between the left and right legs, corresponding to swinging and stance phases. Conversely, the Parkinsonian gait exhibits irregular and poorly synchronized knee trajectories, with inconsistent amplitude and timing across legs. This indicates leg asymmetry and irregular rhythm – hallmark features of Parkinsonian gait.

These detrended visualizations reinforce the potential of depth-based joint tracking as a non-invasive, objective method to characterize gait abnormalities associated with Parkinson’s disease.

Discussion

Significance

Our analysis demonstrates clear and consistent distinctions between normal and simulated Parkinsonian gait based on both joint angle trajectories and depth data. The Parkinsonian trials consistently exhibited a reduced range of motion, as indicated by shallower depth fluctuations, along with bradykinesia, reflected in slower walking speeds. Additionally, these trials revealed irregular timing, hesitations, and abrupt pauses during the sit-to-stand transition, closely mirroring clinically recognized features such as freezing of gait and delayed movement initiation. These observations align with established motor symptoms of Parkinson’s disease and confirm that our system effectively captures key spatiotemporal gait features relevant to PD assessment. The reproducibility of these patterns across subjects underscores the potential of our method as a non-invasive, objective tool for early detection and ongoing monitoring of Parkinsonian motor impairments.

This project introduces a novel, consumer-grade approach to gait analysis by integrating LiDAR depth sensing with vision-based pose estimation. Unlike traditional diagnostic methods that rely on subjective clinical observation or specialized hardware such as wearable sensors and motion capture systems, our system provides a more accessible, low-cost, and scalable alternative. Leveraging the LiDAR capabilities embedded in modern iPads and iPhones, in combination with MediaPipe's lightweight pose tracking framework, we enable accurate 3D joint tracking with minimal setup: no wearables, markers, or controlled environments required. This ease of deployment supports use in real-world settings, including at-home screenings and remote telehealth consultations.

Critically, our system augments standard 2D pose estimation with real-time 3D data, significantly improving robustness against challenges such as poor lighting, occlusions, and non-optimal camera angles. This hybrid approach achieves a balance between affordability and technical precision, making it well-suited for both clinical and non-clinical applications. As LiDAR-equipped mobile devices continue to proliferate, the potential impact and scalability of this gait analysis pipeline will grow, positioning it as a promising solution for accessible neurodegenerative disease screening.

Limitations

While our preliminary findings are encouraging, several limitations must be considered. Most notably, the dataset used in this study was small in size and did not include individuals with a clinical diagnosis of Parkinson's disease. Instead, simulated Parkinsonian gait was performed by healthy participants, which may not capture the full complexity or variability of true Parkinsonian motor symptoms. As such, clinical validation using real patient data is essential to assess the diagnostic sensitivity and specificity of our method. Accessing patient populations for this purpose involves navigating review board protocols, HIPAA compliance, and other regulatory considerations, all of which introduce logistical complexities to large-scale clinical deployment.

Additionally, our system was limited by the technical constraints of the iPad's LiDAR sensor, which operates at a relatively low spatial resolution (192×256 pixels). This can lead to noisy or low-confidence depth frames, particularly at greater distances or under suboptimal conditions. While we employed basic filtering and smoothing techniques to mitigate these issues, further improvements to the data preprocessing pipeline – including more advanced noise reduction, temporal smoothing, and confidence-based landmark weighting – are necessary to ensure reliable and robust feature extraction in varied real-world environments.

These limitations reflect an intentional tradeoff in leveraging a consumer-grade, widely available device for the sake of accessibility and scalability. Although this introduces some performance constraints, the steady advancement of mobile LiDAR technology suggests that the accuracy and reliability of such systems will improve over time, enhancing the viability of this approach for clinical and at-home use.

Next Steps

The promising results of this study lay the groundwork for further development and real-world application of our Parkinsonian gait detection system. A key next step is clinical validation through trials with actual PD patients. Collaborating PD research centers will allow for data collection from individuals at various stages of the disease, which is crucial for evaluating the system's diagnostic accuracy and sensitivity. In parallel, the dataset should be expanded to include a larger and more diverse population, encompassing different ages, body types, and walking patterns to improve generalizability and reduce bias. Longitudinal studies tracking patients over time would also help assess disease progression and response to treatment.

Beyond data collection, future work will focus on automating gait feature extraction – such as stride length, joint asymmetry, and step frequency – and training machine learning models to classify gait as normal or Parkinsonian. This would transform the system into a fully automated screening tool. To improve accuracy and robustness, enhancements to the data pipeline are needed, including better noise filtering, handling of low-confidence LiDAR frames, and smoothing algorithms for more reliable joint tracking.

Finally, while this pipeline was designed for Parkinson's detection, the same methodology could be adapted to support early diagnosis and monitoring of other neurological and movement disorders, such as Huntington's disease, multiple sclerosis, or post-stroke impairments. By building on this foundation, we aim to contribute to a more accessible and objective future in neurodegenerative disease screening.

Conclusion

This project demonstrates the feasibility of using consumer-grade devices, specifically the iPad Pro's LiDAR sensor in combination with MediaPipe pose estimation, to extract clinically relevant gait features indicative of Parkinsonian gait. By reconstructing 3D joint trajectories and analyzing depth and angle patterns over time, we were able to identify key characteristics of Parkinson's disease such as reduced stride length, asymmetry, freezing of gait, and irregular joint motion.

Our results suggest that accessible, non-invasive, and affordable tools can be developed for early detection and continuous monitoring of Parkinson's disease outside of clinical settings. While this study was conducted using simulated Parkinsonian gait, it lays the groundwork for future research with real patient data, larger cohorts, and more advanced feature extraction. As LiDAR hardware continues to improve, systems like the one proposed here have the potential to revolutionize at-home neurological screening and empower earlier, more objective diagnosis of movement disorders.

Sources

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