Enhanced Assessment of Gait Dynamics in Multiple Sclerosis: A Signal Processing Approach for Extracting Range of Motion Using Wearable IMUs

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Abstract: This study investigates the gait dynamics and motor impairment severity in individuals with multiple sclerosis (MS) by analyzing lower limb range of motion (ROM) using data from inertial measurement units (IMUs) collected during the Timed 25-Foot Walk (T25FW) clinical task. Forty-eight participants were categorized into two MS groups based on motor impairment severity (16 MS patients with low motor impairment, 16 MS patients with moderate to severe motor impairment) and 16 healthy control group. IMU raw data of accelerometer and gyroscope from the feet sensors with respect to the lumbar region, were processed using a Butterworth filter and an Extended Kalman Filter to obtain accurate orientation, followed by quaternion to Euler angle conversion for calculating ROM. When the ROM-extracted statistical and time domain features were compared, there were significant differences in ROM characteristics among groups, particularly highlighting the increased variability and reduced control in participants with severe motor impairments. ROM-extracted features such as kurtosis, skewness, and entropy underscored the asymmetrical and irregular motion patterns in advanced MS cases. These findings support the potential of IMU-derived ROM metrics as biomarkers for tracking MS disease progression and tailoring rehabilitation.

1 INTRODUCTION

Multiple Sclerosis (MS) is a chronic autoimmune disorder that affects the central nervous system, leading to a wide range of physical and cognitive impairments. One of the key manifestations of MS is the disruption of motor functions, which can severely impact the quality of life for those affected. Patients with MS often experience muscle weakness, spasticity, and fatigue, all of which can hinder their ability to perform daily activities. These motor impairments lead to a reduction in mobility, increasing the risk of secondary complications such as falls, contractures, and decreased overall functional capacity (LaRocca, 2011), (Heesen et al., 2008).

Gait asymmetry in MS patients can arise from various factors, including spasticity, muscle weakness, or impaired motor coordination. Spasticity, characterized by increased muscle tone and resistance to movement, is a common symptom of MS and can significantly affect gait dynamics (Coca-Tapia et al., 2021; GÜLŞEN et al., 2024).

Range of motion (ROM) is a critical metric in assessing the flexibility and functional capabilities of joints. It quantifies the extent to which a joint can move through its intended motion patterns, providing valuable insights into a patient's musculoskeletal health. In the context of MS, monitoring ROM serves several important purposes, such as assessing mobility, informing personalized rehabilitation, monitoring disease progression, preventing complications, and enhancing quality of life (Soucie et al., 2011).

Wearable devices facilitate real-world patient monitoring and provide valuable biomarkers for symptoms and behaviors associated with gait disorders, thereby enhancing clinical assessments and

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enabling personalized treatment plans (Huang et al., 2024). Recent advancements in wearable technologies and motion analysis techniques, such as inertial measurement units (IMUs), have made it possible to accurately assess ROM in real time. These innovations provide clinicians and researchers with valuable tools to evaluate joint movements in dynamic environments, paving the way for a more comprehensive understanding and management of MS-related motor impairments (Grisbrook et al., 2018), (Blandeau et al., 2023).

Considering the preliminary evidence suggesting potential benefits of exercise programs on lower limb flexibility in MS patients (Torres-Pareja et al., 2019), we believe that a detailed analysis of ROM features will enhance our understanding of these patients' physical capabilities. By extracting and analyzing these beneficial ROM features, we can uncover critical insights into the mobility dynamics of individuals with MS, which may inform and refine treatment protocols. Accurate measurement and monitoring of ROM can facilitate the identification of specific movement impairments and provide objective data that healthcare professionals can use to tailor rehabilitation. Thus, leveraging the advancements in motion analysis technology can play a pivotal role in transforming the management of motor impairments associated with MS, ensuring that therapeutic approaches are both effective and individualized.

In this study, we aimed to process IMU data collected from MS patients during the T25FW test to evaluate their gait and movement patterns. Specifically, we focused on calculating the ROM of the feet relative to the lumbar region, which served as a reference point for assessing the dynamics of lower body movements during walking. This analysis was crucial in identifying and quantifying gait abnormalities in MS patients, aiding in tracking disease progression, evaluating balance and coordination issues, and designing personalized rehabilitation protocols.

2 METHODOLOGIES

2.1 Participants

The study was conducted under a protocol approved by the Koc University Institutional Review Board (2020.418.IRB.157) and all participants provided written consent. We recruited a total of 48 participants, including 32 individuals with multiple sclerosis (pwMS) and 16 healthy controls. The pwMS group was divided into two distinct categories based on their performance in the T25FW task. Group A, comprising 16 patients (7 male, 9 female), completed the T25FW in under 5 seconds, indicating mild motor impairment. In contrast, Group B consisted of 16 patients (3 male, 13 female) with moderate to severe motor impairment, evidenced by a T25FW duration exceeding 9 seconds. The healthy control group included 16 participants (8 male, 8 female) and served as a baseline for comparison. This categorization enabled us to evaluate differences in gait impairment levels among pwMS and to assess the precision of our analytical approach in distinguishing between various stages of motor impairment and healthy gait patterns.

Table 1: Participants Mean T25FW Score and Age.

Mean±SD	Healthy control	Group A	Group B
T25FW duration (seconds)	4.95±0.79	4.24±0.39	14.17±4.31
Age (years)	54.15±12.84	38.01±9.12	56.37±11.47

2.2 IMU Data Collection

In this study, IMU data were collected using the APDM MobilityLab system (APDM Inc., Portland, OR, USA) during T25FW task. IMU data were sampled at a frequency of 128 Hz and the sensors were synchronized in real-time using a dedicated wireless access point, ensuring precise temporal alignment. Data processing was performed using Python for signal filtering, feature extraction and statistical analysis.

For the T25FW, participants walked 7.62 meters as quickly as possible (Figure 1), with the time recorded manually using a stopwatch. Throughout the task, three OPAL sensors (Oregon, USA) were placed on participants' feet and lumbar region to measure spatiotemporal gait parameters, trunk and turning angles, and balance during quiet standing (Figure 2). The system comprised wireless IMU sensors, a docking station, and a wireless access point for real-time data synchronization and transmission.

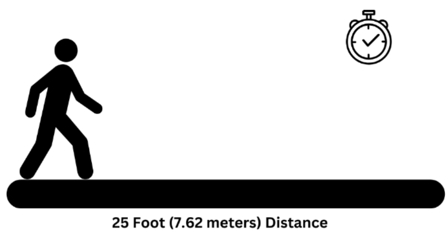

Figure 1: 25 Foot walking Clinical task.

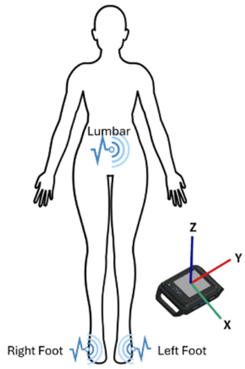

Figure 2: Sensor placement for IMU data collecting.

2.3 Calculation of Range of Motion

A Butterworth bandpass filter with a low cutoff frequency of 0.01 Hz and a high cutoff frequency of 20 Hz was applied to the IMU raw data. For an accurate orientation estimation, an Extended Kalman Filter (EKF) was used. The EKF was implemented to fuse accelerometer and gyroscope data, leveraging their complementary strengths. The prediction step utilized gyroscope data to estimate orientation changes, while the update step corrected these estimates using accelerometer data, reducing the impact of drift and noise. The process equations were based on quaternion kinematics. This iterative approach ensures accurate orientation estimation, particularly in dynamic conditions. This was critical for accurately calculating the ROM from IMU raw data (Senesh & Wolf, 2009), (Das et al., 2018), (Keskinoğlu & Aydın, 2021). Precise orientation data were essential for determining how much the feet rotated relative to the lumbar region during walking. Hence, fused accelerometer and gyroscope data could achieve more accurate 3D orientation estimates for each foot relative to the lumbar region. Initially, quaternions were used to represent orientation due to their ability to avoid gimbal lock, which can occur when using Euler angles. Quaternions offer a more stable representation of 3D rotations, especially when continuous motion is involved, as they do not suffer from the singularities that Euler angles do. However, for more intuitive interpretation and ROM calculation, the quaternions were later converted into Euler angles.

Euler angles were preferred for this study as they provide a clearer, more intuitive understanding of each foot motion relative to the lumbar region, making it easier to interpret and compute ROM in clinically relevant terms (Agnew, 1944). The conversion from quaternions to roll, pitch, and yaw, calculated according to the Equations (2), (3), and (4), ensures mathematical precision, facilitating accurate ROM measurement.

A quaternion is typically expressed as Equation (1):

$$Q = w + xi + yj + zk \tag{1}$$

Where w is the scalar component and i, j and k are the vector components along the x, y, and z axes, respectively (Latimer, 1948). Therefore, the calculation of the three Euler angles (roll, pitch, and yaw) is possible by using quaternion Q=(w,x,y,z), as in the Equations (2), (3), and (4). In this context, roll is the rotation around the X-axis, pitch is the rotation around the Y-axis and yaw is the rotation around the Z-axis (Diebel, 2006).

$$Roll = \arctan(\frac{2(yw+xz)}{1-2(x^2+y^2)}) \tag{2}$$

$$Pitch = arcsin(2(wy - zx)) \tag{3}$$

$$Yaw = \arctan(\frac{2(wx+yz)}{1-2(y^2+z^2)}) \tag{4}$$

The ROM was calculated using a sliding window approach, where each set of Euler angles (roll, pitch, and yaw) was divided into overlapping segments with a window size of 640 samples and a step size of 128 samples, resulting in a 20 percent step size between consecutive windows. This method captures the variability in motion over time by calculating the ROM based on the maximum and minimum values within these 5-second windows, offering a detailed temporal analysis of joint motion. Key phases of gait, such as heel strike or toe-off, which are often impaired in MS patients, are highlighted through this approach. For each window, the ROM was determined as in the Equation (5), by computing the difference between the maximum and minimum values of the Euler angles (roll, pitch, and yaw) for both the right and left feet, relative to the lumbar region. This relative comparison aids in understanding the mobility constraints imposed by MS, and by capturing the variability in joint angles, it provides insights into the functional limitations experienced by MS patients.

$$ROM = \max(joint\ angles) - \min(joint\ angles) \tag{5}$$

2.4 Statistical Analysis

Beyond visualizing ROM patterns, key time-domain and statistical features were extracted to provide a more detailed comparison between groups. These features included the standard deviation, skewness, entropy, peak to peak and time to peak of the ROM values, offering insights into movement consistency, variability, and distribution (Table 2). By analyzing these metrics, we aimed to capture both the magnitude and irregularities in joint motions, enhancing the ability to detect subtle motor impairments in MS patients and provide unique insights into the ROM characteristics across different groups and capture various aspects of gait dynamics. Skewness reflects asymmetry in movement, which is a common biomarker in MS patients, while entropy measures the complexity and irregularity of motion patterns. These metrics collectively provide a comprehensive view of movement variability, motor control, and functional capacity, which are critical for assessing MS-related impairments (Giannakopoulos & Pikrakis, 2014).

Table 2: ROM-extracted features.

Statistical features	Time domain features
Skewness	Peak to Peak
Standard deviation	Entropy
	Time to Peak

3 RESULTS

Figure 3 effectively visualizes comparison of all types of calculated ROM from IMU raw data for both the right and left feet, across the three groups which included to the study. The sub-plots focus on the pitch, yaw, and roll ROM measurements. This visualization serves as a powerful tool to highlight variations in mobility and functionality among the two groups of MS patients and healthy control participants.

According to the Figure 3, the ROM duration is noticeably longer for Group B, indicating that individuals with moderate to severe motor impairment took more time to complete the walking task compared to Group A and the Healthy group. Group B also exhibits greater variability in their ROM patterns, particularly in roll and pitch, reflecting difficulty in maintaining consistent movement and stability during gait. In contrast, the Healthy group consistently demonstrates smoother, more controlled movement patterns across all graphs, with fewer sharp fluctuations and shorter task durations, highlighting superior motor control and balance. Group A shows intermediate performance, with higher initial ROM values in some movements, particularly in Roll and Yaw, but exhibits more variability than the Healthy group. Despite this, Group A maintains better control than Group B, which shows irregular movement patterns with sudden spikes and dips in ROM, indicating a lack of consistent motor control. Additionally, there are notable differences between Right and Left ROMs

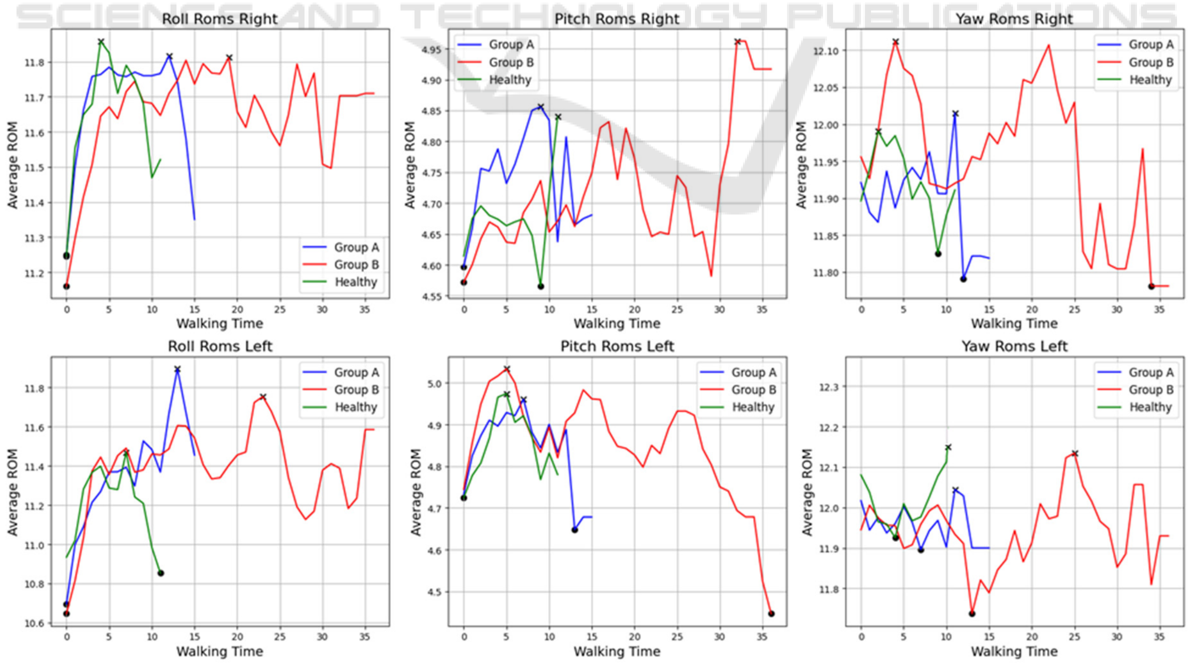

Figure 3: Comparison of extracted types of ROMs for both feet across the three groups *(walking time in seconds and average ROM in degree angles)*.

across groups A and B, with Group B showing greater variability on one side, suggesting asymmetry in movement impairment, pointing to uneven motor function and higher irregularities in roll and pitch ROM compared to Group A and the Healthy group. This trend underscores the progressive impact of motor impairments on walking dynamics and mobility in MS patients and suggest a progressive loss of motor control and balance in advanced MS stages. Additionally, asymmetry between the right and left feet is more pronounced in Group B, reflecting uneven motor impairments

3.1 ROM-Derived Features Extraction

3.1.1 ROM Peak to Peak Value Across the Groups

The peak-to-peak (P2P) ROM measure reflects the difference between maximum and minimum values, providing an indicator of movement amplitude. A higher P2P value suggests increased variability in movement, which may indicate either broader motion capacity or challenges with movement control, particularly relevant in the context of MS-related motor impairments. The corresponding P2P values are presented in Table 3. Group B shows consistently higher P2P values than both Group A and the Healthy group across all ROM dimensions and for both feet. This pattern points to greater fluctuations in movement within the advanced-stage MS group, highlighting reduced control, increased variability, and a lack of stability in rotational movements. In contrast, Group A demonstrates intermediate P2P values, indicating some variability but with relatively more control than Group B, while the Healthy group consistently exhibits the lowest P2P values, reflecting smoother, more controlled movement patterns.

Table 3: The comparison of ROM peak to peak value across the three groups.

Measure	Healthy Controls	Group A	Group B
Right Roll	0.51	0.57	0.59
Right Pitch	0.11	0.17	0.20
Right Yaw	0.06	0.07	0.19
Left Roll	0.43	0.58	0.84
Left Pitch	0.12	0.18	0.29
Left Yaw	0.14	0.18	0.24

3.1.2 ROM Standard Deviation Value Across the Groups

Standard Deviation (SD) quantifies the level of variation or dispersion in ROM data, where a higher SD value reflects greater variability in movement patterns. In this study, examining the dispersion of ROM values is crucial for assessing movement consistency, which is a key indicator of mobility impairment in MS patients. As seen in Table 4, Group B demonstrates higher SD values across five of six ROM types compared to Group A and the Healthy group, highlighting increased variability and reduced movement consistency. This heightened variability likely reflects the challenges in balance and coordination associated with advanced MS, underscoring the progressive impact of the disease on motor control. In contrast, Group A shows moderate SD values, suggesting better control than Group B but with more variability than the Healthy group, which consistently displays the lowest SD values, indicative of smooth and stable movement patterns.

Table 4: The comparison of ROM Standard Deviation value across the three groups.

Measure	Healthy Controls	Group A	Group B
Right Roll	0.08	0.07	0.11
Right Pitch	0.02	0.03	0.04
Right Yaw	0.02	0.03	0.04
Left Roll	0.07	0.09	0.17
Left Pitch	0.03	0.03	0.05
Left Yaw	0.02	0.02	0.05

3.1.3 ROM Entropy Value Across the Groups

As the entropy measures the complexity and unpredictability of the ROM data, higher entropy values suggest a more complex movement pattern, which could be indicative of compensatory strategies in MS patients. Conversely, lower entropy may indicate more stereotyped and less varied movements, potentially reflecting reduced motor function. In our study, Group B consistently shows higher entropy across all ROM types, indicating that their movements are less predictable and more erratic (Table 5). This could be due to a lack of coordination and stability as the disease progresses. Group A shows moderately increased entropy compared to the Healthy group, which makes sense as early-stage MS patients may already experience some irregularities in movement, though not as severe as those in advanced stages. Healthy individuals have the lowest entropy, indicating controlled and predictable movement patterns.

Table 5: The comparison of ROM Entropy value across the three groups.

Measure	Healthy Controls	Group A	Group B
Right Roll	1.14	1.25	3.48
Right Pitch	1.14	1.28	3.48
Right Yaw	1.14	1.25	3.48
Left Roll	1.14	1.28	3.57
Left Pitch	1.14	1.25	3.54
Left Yaw	1.14	1.29	3.54

3.1.4 ROM Skewness Value Across the Groups

As the skewness assesses the asymmetry of the distribution of ROM data, it can help to identify if a particular group has a tendency toward higher or lower ROM measurements. According to Table 6, both Group A and Group B exhibit high negative skewness values in roll ROM, indicating a leftward (negative) bias in their movement distribution. This could suggest that their rolling motions tend to be skewed toward a limited range, potentially due to muscular or motor control issues. Healthy individuals have slightly less negative skewness, indicating more balanced motion distributions. The statistical analysis of ROM data across different groups has revealed significant insights into the movement capabilities of MS patients, particularly highlighting the differences between MS patients with mild motor impairments and patients with moderate to severe motor impairments. The measures of central tendency, variability, energy, complexity, and distribution shape all underscore the functional limitations experienced by individuals with MS. Such insights are crucial for developing targeted rehabilitation strategies aimed at improving mobility and quality of life for patients suffering from this condition.

Table 6: The comparison of ROM Skewness value across the three groups.

Measure	Healthy Controls	Group A	Group B
Right Roll	-1.25	-3.39	-3.64
Right Pitch	-1.88	-2.43	-0.13
Right Yaw	0.71	1.02	1.18
Left Roll	-1.53	-3.81	-2.54
Left Pitch	0.34	-2.70	-0.56
Left Yaw	0.24	0.38	-0.92

3.1.5 ROM Time to Peak Value Across the Groups

The Healthy Group reaches peak ROM the fastest, with notably low times for Right Roll, Right Yaw and Left Roll, which aligns with normal motor control and strength for efficient movement (Table 7). Group B has a longer time-to-peak in most ROM measures (Right Roll, Right Pitch, Left Roll and Left Yaw) indicating that severe MS patients, take longer to reach their maximum ROM. This likely reflects greater challenges in motor control and muscular strength.

Table 7: The comparison of ROM Time to Peak value across the three groups in seconds (s).

Measure	Healthy Controls	Group A	Group B
Right Roll	4	12	19
Right Pitch	11	9	32
Right Yaw	2	11	4
Left Roll	7	13	23
Left Pitch	5	7	5
Left Yaw	11	11	25

4 DISCUSSIONS

4.1 Interpretation of the Results from Clinical Perspective

Overall, the extracted features clearly illustrate that Group B, which represents individuals with severe motor impairment, demonstrated more pronounced and significant differences in their ROM characteristics when compared to Group A and Healthy group, and showed highly irregular ROM patterns, particularly in Roll movements, where sharp peaks and drops are evident. Group A demonstrates more stability than Group B but less control than the Healthy group. This observation is logical, as advanced stages of MS are typically associated with greater functional limitations and variability in movement patterns, leading to a more evident expression of motor deficits. Interestingly, while Group A is characterized by lower motor impairment, it consistently exhibited intermediate values across in most extracted features such as standard deviation, peak to peak, entropy. This indicates that even in the early stages of MS, individuals may experience subtle yet meaningful variations in their movement patterns that can be overlooked in traditional clinical assessments. Group A patients, as the early-stage patients tended to complete the task with increased speed and exerted additional effort, likely as an attempt to demonstrate their ability to perform certain movements with ease. The presence of these intermediate values highlights the importance of utilizing quantitative measures to capture nuances in motor performance, as reliance on observable changes alone may lead to an underestimation of impairments. Overall, our findings underscore the utility of detailed ROM assessments in differentiating movement patterns among various stages of MS.

From a clinical perspective, the ROM metrics analyzed in this study provide actionable insights into motor impairments in MS patients. The increased variability and entropy observed in Group B may indicate a need for targeted interventions aimed at improving balance and coordination. Similarly, the asymmetrical gait patterns highlighted by skewness metrics could guide clinicians in tailoring rehabilitation programs to address specific motor deficits. By integrating these objective measures into routine clinical practice, healthcare professionals can enhance the accuracy of disease monitoring and personalize treatment plans.

Comparing these results to earlier studies on MS and mobility limitations, this study uniquely quantifies ROM variability calculated from IMU raw signals, providing a more granular view of the asymmetrical and erratic movement patterns in patients with MS by extracting different time domain and statistical features. In contrast to prior research, which primarily relied on the directly reported spatiotemporal gait parameters provided by IMU recording systems, our study adopted a more sophisticated approach by independently processing the raw IMU signals to extract ROM metrics. Rather than depending solely on system-generated parameters, we applied signal processing techniques, including quaternion to Euler angle conversion, to obtain precise, real-time ROM measurements. This methodology allowed us to capture nuanced joint motion patterns, providing a more granular analysis of movement dynamics, which may reveal subtle variations in mobility that standard IMU reported parameters could overlook. The ROM metrics explored here, such as peak-to-peak, entropy, kurtosis, and skewness, provide clinicians with an enriched understanding of MS patients' movement consistency and variability. For patients with moderate to severe impairment, the ability to detect high variability and asymmetrical movements could support targeted physical therapy interventions, aiming to improve balance and reduce fall risks. Additionally, this study suggests the potential role of IMUs and ROM analysis in developing predictive models for motor function decline in MS, which can assist clinicians in modifying treatment strategies.

MS disease classification primarily rely on spatiotemporal gait parameters, such as step length and walking speed, reported by IMU systems, which often lack the sensitivity to detect subtle motor impairments. However, this study introduces a novel approach that leverages ROM-based metrics which capture the variability, complexity, and asymmetry in gait dynamics and by incorporating these features, this study aims to enhance the sensitivity and specificity of MS disease classification.

4.2 Limitations

While the study presents promising results, limitations include the small sample size and potential variability in sensor placement, which may influence ROM accuracy.

5 FUTURE DIRECTIONS

Future research could expand on this work by incorporating a larger, more diverse patient population and exploring longitudinal ROM changes post-rehabilitation to assess therapy efficacy. Further, integrating machine learning techniques with ROM metrics could enhance the predictive power of these measures, potentially leading to automated, real-time analysis in clinical settings.

6 CONCLUSIONS

In conclusion, our analysis of range of motion (ROM) features and their visualizations has significantly enhanced our understanding of the differences among the three participant groups. Group B's heightened ROM variability reflects impaired motor control, which is consistent with prior research linking advanced MS stages to increased motor instability and reduced gait consistency. These findings underscore the potential for using ROM metrics as biomarkers for tracking MS progression and tailoring rehabilitation approaches. By identifying and analyzing these subtle differences, clinicians can improve diagnostic accuracy and better tailor interventions to meet the specific needs of patients at different stages of the disease, ultimately enhancing their mobility and quality of life.

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