

Remote Gait Monitoring System to Facilitate Assessment of People With Multiple Sclerosis

Joaquín Ordieres-Meré[✉], Senior Member, IEEE, Mercedes Grijalvo[✉], Guillermo Martín-Ávila, and Yolanda Aladro

Abstract—Gait impairment is among the most common and affecting symptoms of multiple sclerosis (MS), occurring in more than 90% of patients as the disease progresses. Conventional clinical tests, such as the timed 25-foot walk (T25FW), are not always able to capture the entire richness of gait impairment, especially in everyday settings. To overcome these shortcomings, this article introduces a new remote gait monitoring system based on wearable smart socks embedded with inertial sensors. The system continuously receives high-frequency motion data and, therefore, enables gait auto-recognition and can improve the classification of MS-associated gait impairment. An end-to-end pipeline for data processing was developed, which involves sensor fusion techniques, semantic gait modeling, and machine learning classification. The segmentation and characterization of gait are performed using the spectral analysis of accelerometer and gyroscope signals, with short-time Fourier transform (STFT)-based feature extraction to identify the periodicity and quality of gait. In addition, a deep learning (DL) approach based on the combination of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks is used to discriminate walking patterns with high precision that help detect abnormalities related to MS. Experimental validation was carried out on a population of people with MS (PwMS) and healthy controls, with our model achieving an average accuracy of 97.10% and an area under the curve (AUC) of 0.99 for severe MS classification. The Internet of Wearable Things (IoWT) paradigm introduced here continuous data acquisition and integration with other wearable sensors and offers a noninvasive and scalable solution for continuous gait monitoring. The results highlight the potential of this approach to improve clinical examination, enable early detection of mobility decline, and support individualized rehabilitation planning. Future studies will explore the incorporation of transformer-based artificial intelligence (AI) models to further improve the classification of MS disability.

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Joaquín Ordieres-Meré and Mercedes Grijalvo are with the Universidad Politécnica de Madrid, 28006 Madrid, Spain (e-mail: j.ordieres@upm.es; mercedes.grijalvo@upm.es).

Guillermo Martín-Ávila is with the Hospital Universitario de Getafe, 28905 Getafe, Spain (e-mail: guillemartinavila@gmail.com).

Yolanda Aladro is with the Multiple Sclerosis Unit, Hospital Universitario de Getafe, 28905 Getafe, Spain, also with the Universidad Europea de Madrid, 28670 Madrid, Spain and also with the Research Group, IdiPaz, 28029 Madrid, Spain (e-mail: yolanda.aladro@salud.madrid.org).

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I. INTRODUCTION

MULTIPLE sclerosis (MS) is a chronic, inflammatory, and neurodegenerative disease of the central nervous system, affecting mainly young adults and causing their disability. According to the International Federation of MS Atlas in its third code edition, approximately 2 900 000 people with MS (PwMS) live worldwide, including approximately 700 000 in Europe and 55 000 in Spain [1], [2]. Each year, more than 2000 new cases are diagnosed in Spain. MS often begins between the ages of 20 and 40 years [3], [4].

Gait disturbances are the main cause of disability progression in MS and present in more than 90% of patients [5], [6]. The diagnosis and monitoring of progression are based on the expanded disability status scale (EDSS) and the timed 25-foot walk (T25FW) tests, both with rather low sensitivity and reproducibility, resulting in delayed diagnosis and poor treatment optimization [7]. Although conventional gait parameters provide a valuable snapshot of mobility, this study introduces a novel approach that focuses on the continuous, frequency-based characteristics of gait signals, which we argue are more ecologically valid for remote, long-term monitoring of PwMS in their daily lives. For PwMS, changes from baseline in T25FW over 20% are generally considered clinically significant [8], [9]. These tests have several limitations that make them an incomplete measure of overall gait function. One of its primary drawbacks is that it only evaluates short-distance walking, providing little insight into endurance and the ability to maintain mobility over longer periods, which is crucial for daily activities. Furthermore, it may not be sensitive enough to detect mild impairments in individuals with early-stage MS, as they can often complete the test within normal time ranges, limiting its usefulness in identifying subtle gait dysfunctions [10].

Although these limitations of conventional assessments are well-documented, a growing body of research has demonstrated the potential to enhance these tests by adding wearable sensors. By doing so, clinicians can obtain objective and quantitative data on patient walking performance during these structured tasks. However, even with the addition of sensors, these tests are performed in a controlled clinical setting, providing only a limited snapshot of a patient’s mobility. They do not capture the variability, fatigue, and compensatory

mechanisms that manifest throughout a patient's day in their natural environment. To truly understand how MS affects mobility on an everyday level, a more ecologically valid assessment is necessary.

Another significant limitation of T25FW is its inability to assess fatigue, a major symptom in MS that can severely affect mobility over time. Since the test is very brief, it does not capture the progressive decline in walking ability that may occur with prolonged activity. Similarly, it does not provide a comprehensive analysis of gait, as it does not take into account factors such as balance, coordination, and compensatory walking mechanisms that are often present in individuals with MS [11]. The test results can also be influenced by external factors such as surface conditions, the use of assistive devices, and patient motivation, leading to variability in the outcomes. Furthermore, it is subject to ceiling and floor effects, as those with mild MS can perform at near-normal speeds, making it difficult to detect meaningful changes, while those with severe disability who cannot walk cannot complete the test, rendering it ineffective for nonambulatory PwMS [12].

Although the EDSS provides a helpful snapshot of neurological impairment in MS, it does not provide a full picture of one's mobility. To get the full picture, clinicians will rely on a variety of tests. When a patient comes for their follow-up, the doctor performs the EDSS, noting their level of disability. But to truly understand how MS affects your mobility on an everyday level, a further detailed assessment is necessary. The physician may require the patient to perform the 6-min walk test (6MWT), which measures the distance they can walk in 6 min, assessing their endurance and functional walking capacity. Then, the timed up and go (TUG) test might be used. This simple test aims to evaluate their dynamic balance and coordination, both of which are necessary to perform daily tasks [13]. However, these other assessments, while useful, are not so convenient in a hectic clinical setting. In accordance with American Thoracic Society (ATS) guidelines, the 6MWT is recommended to be conducted on a 30-m (100 ft) straight course to minimize turns and ensure comparability of results [14], [15], [16]. Although shorter walkways (e.g., 25 ft) have been employed in certain studies under spatial constraints, such adaptations can lead to reduced distances due to increased turning frequency and should be interpreted with caution when compared to ATS-standard results [17]. Similarly, the TUG and gait analysis often have to spend considerable amounts of time performing and interpreting, potentially disrupting patient continuity of care. Therefore, while these tests are informative for the evaluation of MS mobility, clinicians must balance their use with careful consideration against the practical needs of their own clinical environment.

The use of wearable technology to measure gait dysfunction in PwMS in nonclinical settings is a proposition that is supported by an overwhelming amount of empirical evidence. The reasoning is as follows. MS tends to exhibit gait dysfunction, and monitoring the changes is vital in the disease's management. Conventionally, this has meant face-to-face evaluation by a neurologist, typically specialized hardware in the laboratory. However, these measures over time are not

necessarily an accurate reflection of the overall assessment of a patient's ability to walk on a daily basis, a measure known as ecological validity. From approximately 2018, there has been increasing research that validates wearable sensors, such as those contained in smartwatches, insoles, or small devices worn by the person, as an accurate means of quantifying important gait parameters. Research conducted by Di Flumeri et al. [18] and Tipton et al. [19] has shown that these sensors are capable of precisely recording parameters such as walking speed and cadence, with close correlation with the values recorded using widely recognized laboratory equipment. These tools are more than basic assessment instruments; they can detect subtle changes and differences in gait, as seen by Soltani et al. [20], and can possibly become early markers of disease progression.

The focus, then, turns to how these tools can be applied in practical situations. Research, such as that by Briggs et al. [21], indicates that PwMS typically have the willingness and ability to use these sensors at home, following normal monitoring protocols. This is a significant benefit, allowing for continuous or routine data collection in the context of a patient's daily environment.

The long-term advantages of this change are enormous. The ongoing monitoring process enables early detection of subtle gait changes, hence more timely interventions; this concept is further explored by Sparaco et al. [22] and Salaorni et al. [23]. Second, the collected comprehensive data can be used to guide the development of personalized treatment regimens and rehabilitation protocols, with interventions adapted to the individual needs of the patient [24]. Furthermore, remote monitoring can help minimize the need for regular face-to-face clinic appointments, alleviating the burden on both patients and the healthcare system [25].

A set of wearable inertial sensors can provide objective and reliable measures of gait disturbances and constitute potentially useful tools to monitor clinical progression in prospective cohorts of patients, both under laboratory conditions and during daily activities [22]. Wearable devices can detect physical condition, use real-time perception, compare and analyze a large amount of data for analysis, interpretation, and response, and can then select the most appropriate current processing and support [26].

Based on the above, evaluating and quantifying walking in the community for longer periods of time would be a more ecological approach, reflecting better the functional interference of its impairment in the quality of life of PwMS. Therefore, this article explored how inertial sensors could provide objective and reliable measures of gait disturbances and constitute potentially useful tools for monitoring clinical progression in prospective cohorts of patients, both under laboratory conditions and during daily activities.

To achieve this goal, we adopted a new generation of wearable smart socks that provide an extensive inertial measurement unit (IMU) with 12 channels, including pressure sensors for the feet. A specific information technology (IT) framework was developed to handle the collected information, as it was relevant for data analysis and for usability when



Fig. 1. Sensoria Inc. smart socks with IMU and three pressure sensors per foot (S0–S2), used as the main wearable platform.

fusing with other sensors (see Fig. 1). Support for the digital usage of technology by patients has previously been evaluated [27], [28]. Within the framework, the identification of the EDSS for PwMS based on such datasets will be further analyzed.

II. STATE OF THE ART

Currently, wearable devices are more likely to be purchased by individuals who already lead a healthy lifestyle and want to quantify their progress [29]. Most wearable manufacturers (e.g., Fitbit and Nike) stress the potential of their devices to become an “all-in-one” platform to improve physical performance and positive habit formation [30]. The main vision is that wearable devices with sensors transform care by moving from manual transfer of subjective self-reported information to an integrated, longitudinal, minimally intrusive, and interactive sharing of data based on the ecology of a person in their natural settings [31]. It is mobile health (mHealth) as a key component of connected health and technology-enabled care (TEC) [32]. In MS, the experience with such devices is limited [22], [26], but laboratory-based gait assessments detect subtle deficits in gait quality in the early stages, even without subjective functional alterations [23], [33].

Although the metrics obtained in the clinical setting basically provide a static snapshot, they could be useful to predict and detect progression in longitudinal studies. Although preliminary studies such as [34] and [35] have indicated that simple quantification of gait, including stride length and walking time, yields valuable indicators of disease severity in MS, the importance of employing more sophisticated spatial and temporal parameters in assessing changes in motor function is increasingly appreciated. Stride length is a significant parameter that reflects the capacity of PwMS to maintain coordinated movements; notably, shorter stride lengths tend to reflect improvements in disease progression and higher levels of disability. In addition to stride length, research emphasizes the importance of gait velocity, cadence, and variability [36]. Flachenecker et al. [33] show that it is possible with wearable

sensors to continuously monitor these parameters, unmasking subtle changes in the pace of walking that can denote a reduction in motor function prior to clinical onset. These devices have proven useful in evaluating different spatiotemporal gait parameters in the laboratory setting and, even more relevant due to their ecological validity, in quantifying ambulation during prolonged monitoring in real-life settings. They have shown clinical utility in Parkinson’s disease, cerebellar disorders, stroke, and other processes.

Step symmetry is another key feature that quantifies the degree of coordination of the lower extremities. Step length or timing inconsistencies have been associated with motor dysfunction after MS, as demonstrated by Müller et al. [17] through a study in which they depicted the progression of gait asymmetries with the progression of the disease. In addition, the research by Psarakis et al. [37] emphasizes the role of compensatory gait mechanisms and instability, specifically related to fatigue, which is a prevalent symptom of MS. For example, increased postural sway and decreased ankle dorsiflexion are signs of compromised balance and an increased risk of falling. In addition, Abbadessa et al. [38] explore the usefulness of wearable biosensors in tracking alterations in gait patterns, allowing medical professionals to identify deviations from a patient’s norm and perform interventions on time. In general, although step count and walking time alone are valuable markers of mobility patterns, the addition of parameters such as stride length, gait speed, step symmetry, cadence, and postural stability allows a more sensitive assessment of MS development. These additional gait parameters enhance the validity of remote monitoring, and wearable sensors have emerged as an increasingly effective means of tracking motor function impairment in PwMS.

Wearable IMUs for motion sensors are made up of accelerometers and/or gyroscopes that measure linear acceleration and angular velocity and record body movement in the three axes of space. They are shown to be reliable, sensitive, and inexpensive assessment tools that have a growing application in gait analysis [39], [40], and other movement disorders [41], [42], [43] in the field of neurology. A recent study by Zahn et al. [44] further validates this, demonstrating a high degree of agreement between IMU-derived spatiotemporal parameters and those obtained from gold-standard marker-based motion capture systems during walking in PwMS. These devices have proven useful in evaluating different spatiotemporal gait parameters in the laboratory setting and, even more relevant due to their ecological validity, in quantifying ambulation during prolonged monitoring in real-life settings.

They have shown clinical utility in Parkinson’s disease [42], [45], cerebellar disorders [40] or stroke [46], and other processes. The ability of IMUs to estimate position during gait is rooted in the principle of dead reckoning, where acceleration data from the device are double-integrated over time to estimate displacement. However, this approach is susceptible to drift errors due to noise accumulation, which requires error correction techniques such as zero-velocity updates (ZUPTs) or Kalman filtering [17]. In particular, step-length estimation, a valuable parameter of gait analysis, can

be enhanced with step detection algorithms that exploit the periodicity of the accelerometer signals. It enables accurate monitoring of mobility impairment in progressive diseases such as MS.

However, orientation estimation is based on sensor fusion algorithms such as Madgwick or Mahony filters, which use a combination of gyroscope and accelerometer data to allow drift-free orientation tracking [47]. Gyroscopes are very sensitive to rotations, but tend to drift in the long term; accelerometers address this issue by offering a gravity reference. Furthermore, the inclusion of magnetometers can be utilized to improve heading estimation, especially where there are negligible external magnetic disturbances [33]. Fundamentals of the mathematical support for identification of the step length are included in Appendix A.

Recent advances in transformer-based architectures have substantially enhanced gait analysis by improving the capacity to model complex spatiotemporal dependencies in human movement data. In particular, Le and Pham [48] proposed a spatiotemporal transformer network to estimate critical gait parameters, such as walking speed and gait deviation index, directly from RGB video streams, demonstrating significant improvements over convolutional neural network (CNN)-based baselines while reducing manual feature engineering efforts. Similarly, Dinh et al. [49] introduced a dual-input convolutional transformer system that accurately infers gait indices using single-view video recordings, validating its utility in clinical environments with limited resources. Cosma et al. [50] developed GaitFormer, a transformer-based model trained with noisy multitask learning on the DenseGait dataset, showing strong generalization and outperforming traditional models even without manual annotation. Complementing this, Nguyen et al. [51] explored the use of transformers in 1-D inertial signals for Parkinson's gait detection, noting both higher classification performance and better stability compared to recurrent models.

Beyond recognition, generative transformer architectures like GAITGen [52] have been introduced to synthesize realistic gait sequences conditioned on pathology severity, enriching clinical datasets and improving downstream task performance. Moreover, Basoc et al. [53] explored SetTransformers for dataset-agnostic gait enrollment, demonstrating scalable transformer-based modeling under open set recognition settings. These studies collectively establish transformers as powerful tools for modeling gait patterns in clinical and general domains.

Recent years have witnessed a surge in the application of deep learning (DL) and the Internet of Things (IoT) for remote gait analysis, particularly in telemedicine contexts. Sarkar [54] presented a hybrid CNN-long short-term memory (LSTM) architecture for wearable-based gait recognition, achieving robust performance in free-living scenarios. Other works have integrated attention mechanisms with multimodal wearable sensors to enhance gait quality prediction within the IoT-driven frameworks [55]. These studies underscore the growing synergy between deep learning models and sensor-rich wearables for continuous mobility monitoring.

Our framework is also designed to be compatible with cutting-edge machine learning techniques that are pushing the boundaries of gait analysis. Recent advances in transformer-based architectures have substantially enhanced gait analysis by improving the capacity to model complex spatiotemporal dependencies in human movement data. In particular, Le and Pham [48] proposed a spatiotemporal transformer network to estimate critical gait parameters. These studies collectively establish transformers as powerful tools for modeling gait patterns in clinical and general domains. The discussion of these advanced models demonstrates the scalability and forward-looking nature of our proposed platform. This work, which focuses on detecting and characterizing real-world gait behavior using spectral analysis and time–frequency representations derived from wearable IMU data, is complementary to these advanced pipelines. The semantic modeling of gait events, independent of disease classification, positions our approach as complementary to transformer-based pipelines. Furthermore, our proposed framework lays the groundwork for future integration of transformer models to enhance gait segmentation and severity estimation, while maintaining interpretability and ecological validity in unconstrained environments.

III. METHODS

In this article, a top–down approach has been adopted to address the integration of heterogeneous data streams from multisource wearable devices. It is strongly applicable since it addresses the need for the unification of data on various hierarchical levels of entities of the gathered information. On this basis, an exemplar conceptual framework is demonstrated to comprehensively structure the remote monitoring process.

The second phase describes the data collection method that was used, detailing the acquisition and preprocessing of raw sensor data. Data fusion was then performed, with a focus on IMU data and GPS signals to improve motion-tracking accuracy. Finally, the proposed analysis pipeline was implemented. It began with the segmentation of gait cycles and was followed by the development of a disease identification algorithm that used the extracted gait features for diagnosis and classification.

This section is a bit dense, and to facilitate the understanding of all the involved components, a graphical aid is proposed (see Fig. 2).

A. Data Collection

After an intensive analysis of the available wearable devices, we have selected two instrumented smart socks from Sensoria Inc. (Sensoria Health Inc., Seattle, WA, USA) [56], having as an advantage against other providers the integrated information from accelerometer, magnetometer, gyroscope, as well as the inclusion of three pressure sensors per individual sock. They have made available technical specifications, which allow us to develop our own data capture application running on an Android mobile phone [57] grabbing 12 channels of data (three components of the magnetometer vector, three for the acceleration vector, three for the gyroscope vector, and three

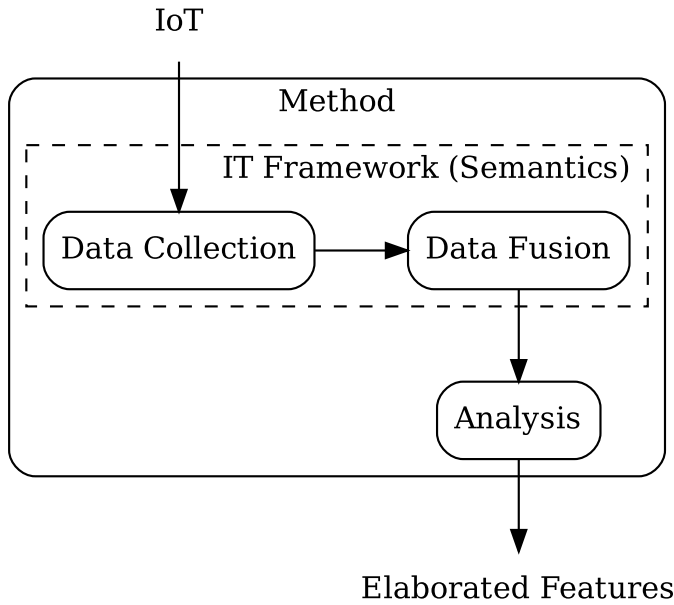


Fig. 2. Logical pipeline of our framework. It shows how semantic structuring at the IT layer ensures that low-level sensor data (socks, GPS) can be fused and transformed into clinically meaningful gait features.

pressure signals) with a frequency between 45 and 55 Hz. This sampling frequency enables one to accurately describe the walking structure.

According to the proposed framework (Fig. 4), the hub layer adds information relevant to position, leg, and software version. Data compression and delivery are then performed to the cloud, where an Influx DB time-series database [58] was selected to store the collected data. All these functions have been integrated into an app (developed both for Android and iOS) to facilitate access to the service [59].

Our current dataset includes a modest number of subjects, with 35 PwMS and 12 healthy controls monitored for one day each. This population represents a variety of ages and both sexes, but is not explicitly stratified by the EDSS severity categories. The main focus of this study is the methodological development and initial demonstration of discriminative sensitivity in the analysis of gait patterns. The extensive data acquired per participant, which encompasses multiple hours and varied daily activity patterns, substantially enhances the dataset's effective size and variability. This allows us to robustly evaluate our power spectral density (PSD)-related algorithm's potential discriminatory power at a preliminary stage. Ongoing work involves active data collection with expanded cohorts and structured clinical stratification to rigorously confirm and further refine the clinical applicability of our gait analysis approach.

The collected data can be reviewed using a Grafana dashboard (see Fig. 3), but this is just a view of the raw data.

Based on raw data collected at high frequency, the traditional MS assessment looks to estimate a set of gait-based features derived by combining the raw sensor data and the calculated orientation. The orientation is essential to transform the accelerometer data from the sensor frame to the global frame (or a consistent body frame), allowing for integration.

Then, for the gait process, the full walking cycle starts when the heel contacts the ground. Key events, including initial contact, toe off, feet adjacent, and tibia vertical, mark the phase shifts. For each foot, the full walking cycle starts when the heel contacts the ground. The stance process for each foot is divided into three phases: loading response (LR), midstance (MSt), and terminal stance (TSt). While one foot is in its stance process, the opposite foot is in its swing process, which includes the phases of preswing (PSw), initial swing (ISw), mid-swing (MSw), and terminal swing (TSw). Phase labeling, where the phases of LR, MSt, TSt, PSw, and ISw are defined as G0–G4, and the phases MSw and TSw are combined as G5 [60]. All these elements are detailed in Appendix B.

The features mentioned above were gait-specific and required the integration of information. However, this article estimated the level of MS disease not by directly reporting these individual parameters but rather by analyzing the harmonic properties of the acceleration, gyroscope, and pressure signal modules to identify characteristic spectral features that correlated with the status of the disability.

Nevertheless, since individuals perform various activities in the course of their day-to-day lives, the primary analytical challenge is the segmentation of continuous motion data into walking periods, thus defining a semantic model of gait events. However, in contrast to the more traditional feature-oriented approach, this article aims to estimate the level of MS disease by analyzing the harmonic properties of the acceleration, gyroscope, and pressure signals modules.

The proposal is to use a dynamic short-time Fourier transform (STFT) operator (by combination of sensor signals with a Hamming window) in the range of 5 Hz to characterize gait behavior. Therefore, the analysis of the accelerometer and gyroscope module allow us to identify the walking process, while the hierarchical analysis of pressures shows the quality of walking. The Hamming window was used because it has been extensively utilized to minimize spectral leakage without losing frequency resolution in the time–frequency plane. Gradual tapering of the window reduces discontinuities at the edge of the window, a very sensitive parameter for accurately delineating gait cycles in the quasi-periodic walking motion signal [61]. The window length was fixed at 7 s to compromise between time and frequency resolutions based on standard protocols for gait analysis using STFT. This period encompasses several stride cycles (usually six–ten steps for a nominal gait frequency of 1 Hz), without compromising temporal localization, allowing robust frequency representation. An overlap of 50% was used to enhance continuity between windows and facilitate the detection of transient events, as suggested in research on wearable sensors on human movement [62], [63].

The chosen 0–5-Hz frequency range is based on the physiological bandwidth of human gait. Normal walking frequencies for healthy adults are typically between 0.6 and 2 Hz, with higher order harmonics up to approximately 3–4 Hz depending on cadence and biomechanical variation [64]. Therefore, the 5-Hz upper limit provides a sufficient buffer to include relevant gait dynamics, including asymmetries and irregularities, especially prevalent in PwMS. STFT analysis confirmed that



Fig. 3. Grafana dashboard view of raw gait data showing pressure, acceleration, gyroscope, and magnetometer streams. The highlighted point corresponds to G0, the LR phase of the stance time (see Appendix B). The pressure data clearly illustrate the step structure, while the magnitudes of the acceleration and gyroscope readings ($\|Accel\|$ and $\|Gyroscope\|$) also exhibit characteristic behavior for steps.

most of the spectral energy of the gait patterns is indeed concentrated below 2 Hz, as expected clinically and reaffirming our design decision (refer to Sections III-D and IV).

B. IT Framework

As previously discussed, due to the requirements for data sampling and integration with other wearable devices, there is a demand for a more comprehensive conceptualization of wearable data in the complex semantic context of human behavior in their daily activities. To allow enough flexibility, a comprehensive framework is proposed (see Fig. 4).

The communication limitations exhibited by the wearable devices forced developers to rely on personal hubs, with different devices connected by the Bluetooth protocol to the smartphone [65], [66]. However, cutting-edge 6G technologies are designed to facilitate the cellular IoT connections and services such as long-range low-power communication (LRLPC), ultrareliable low-latency communication (URLLC), and in-network intelligent computing services (INICS). The findings demonstrate that these technologies are well-suited to the requirements of the Internet of Wearable Things (IoWT) [66].

It enables the concurrent operation of various wearable devices, reflecting a prevalent trend in the current landscape. Therefore, there are also ongoing requirements concerning multisensor and multicloud architectures that cater to various

types of wearable devices, all while facilitating the semantic definition of data flows using the appropriate ontology. Furthermore, the need for versatility to perform computations both on the edge and within the cloud infrastructure remains imperative [67].

Consequently, our framework is designed to handle multiple physical layers from different sources. This includes multiple sensors within a single device (e.g., the IMU and pressure sensors in our smart socks) as well as data from multiple wearable devices (e.g., smart socks and a smartwatch), which can all converge at a personal hub. This hub is responsible for preliminary data processing and subsequent submission to the relevant cloud platform, depending on the device manufacturer or the specific data collection application used. In this way, an effective integration of the data can be done, facilitating the end points to obtain all the relevant information [68].

The next pivotal element involves the development of the ontology according to the data source. This necessitates careful attention to establish sufficient connections between entities to adequately define them and facilitate interactions between them. This approach allows for the federation of entities and ontologies, facilitating the creation of an attribute network.

The ontological federation and entity federation are the unification of diverse, autonomous datasets and knowledge structures into a single, unified structure that allows seamless interoperability. In numerous complicated systems where

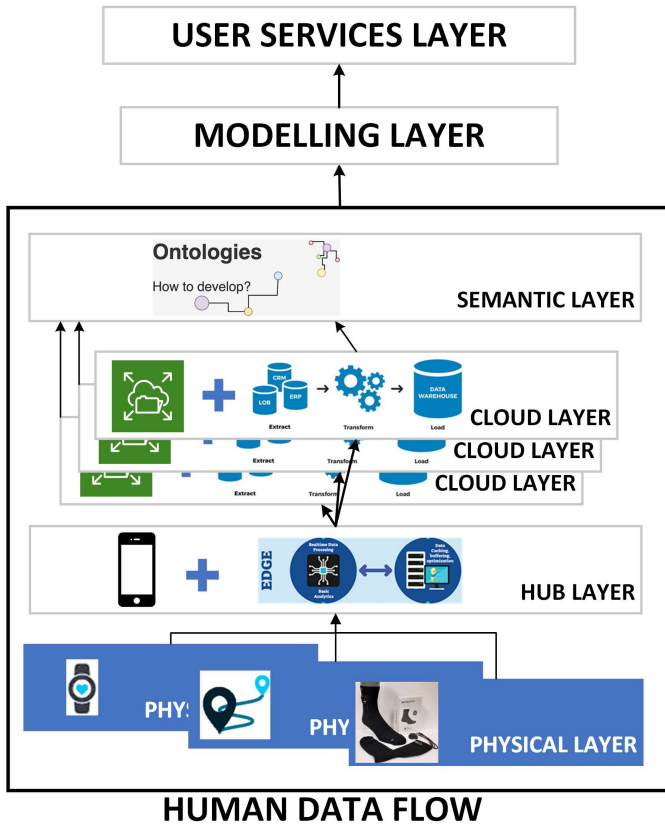


Fig. 4. IT framework for integrating heterogeneous wearable data sources across physical, hub, cloud, and semantic layers. This framework's flexible and scalable design is crucial for enabling the continuous, ecologically valid, and detailed remote monitoring of gait required for a comprehensive assessment of MS.

data are collected from heterogeneous source, such as the IoWT sensors, enterprise databases, biomedical records, or sensors—interentity consistency and semantic coherence are crucial. Ontologies allow for routine description of knowledge by defining concepts, their attributes, and interdependencies, allowing for standardized interpretation of data and reasoning [69].

By federating entities and ontologies, an attribute network can be established. This network encapsulates the relationships between different attributes in different domains and forms an interconnected system that supports advanced reasoning, data fusion, and predictive analytics. Each entity within this network possesses a set of attributes, which may be sensor measurements, contextual metadata, historical trends, or derived computational attributes. These attributes are related among entities according to ontologically specified semantic relationships, allowing intelligent data correlation and inference [70].

In practical application scenarios, such a feature network can facilitate context-sensitive analysis and dynamic knowledge discovery. For example, the ontological federation of the IoT devices, environmental conditions, and structural health issues can enable real-time anomaly detection for smart infrastructure monitoring. Lastly, the ontology federation and entities improve the interoperability, scalability, and semantic

density of the data, and the generated attribute network is a graph-based structure that can be compatible with advanced analysis applications [71].

The specific nature of these relationships will depend on the case being analyzed, and as such, they may not be identifiable at the point of initial cloud data injection, but may become apparent in subsequent stages.

C. Data Fusion

IMUs provide high-rate motion tracking using only accelerometers, gyroscopes, and magnetometers, which report real-time estimates of orientation and position. As mentioned in Section II, velocity and position are estimated by integrating acceleration, with contributions from the gyroscope and magnetometer data for orientation. However, this process is prone to drift, significantly degrading the accuracy of the derived positions.

The work of Kassas et al. [72] highlights the potential to reduce such errors by incorporating external reference data, such as GPS signals.

GPS, by contrast, provides global position tracking, albeit at a much lower sampling rate and subject to errors in urban regions where satellite signals are liable to be obscured. By merging GPS and IMU data, the system leverages the high accuracy of GPS for long-term position estimation and overcomes its low update rate using IMU-derived velocity and orientation estimates. This fusion has been described in the monitoring of mobile mobility for MS and other neurological conditions [73], where the fundamental mathematical tool has been incorporated in the Appendix A.

The integration of GPS and IMU is generally achieved by Kalman filtering or complementary filtering techniques. Kalman filters dynamically change the weighting between IMU and GPS measurements relative to estimated uncertainty for smoother and more precise trajectory estimation. Some literature, for example, Liu et al. [74], illustrates how sensor fusion can be extended to include other data streams, such as barometric measurements, to further improve motion tracking, particularly in settings with poor GPS coverage.

The Mahony filter output is the orientation, represented as a quaternion [see (11)]. Quaternions are preferred over Euler angles (roll, pitch, and yaw) to circumvent issues such as gimbal lock and singularities. The filter algorithm proceeds in two primary stages: prediction and update. In the prediction stage, the gyroscope data are integrated to estimate the change in orientation over the sampling interval. The update stage leverages accelerometer and magnetometer data to correct for gyroscope drift. The accelerometer, which measures gravity, provides a reference for pitch and roll. The filter calculates the expected direction of gravity in the IMU's frame based on the current estimated orientation and compares it to the measured acceleration vector. Similarly, the magnetometer is used, and the expected magnetic field vector is compared to the measured vector, providing a heading correction. The error, e , is computed using the cross-product

$$e = (a \times g) + (m \times b) \quad (1)$$



Fig. 5. Trajectory comparison showing that sensor fusion eliminates IMU drift and smooths GPS noise. This demonstrates the reliability of our fusion approach for clinical mobility tracking.

where b is the normalized magnetic field vector $[b_x, 0, b_z]$ (tilt-compensated), and a and m are the normalized accelerometer and magnetometer measurements in the sensor frame, respectively.

A proportional–integral (PI) controller is employed to correct the gyroscope bias. The error, e , is multiplied by a proportional gain (K_p) for immediate correction, and integrated over time and multiplied by an integral gain (K_i) to address the accumulated bias. The integral term, e_{int} , is updated as

$$e_{\text{int}}(t) = e_{\text{int}}(t-1) + e * \Delta t. \quad (2)$$

The total correction term is as follows:

$$\omega_{\text{corrected}} = \omega + K_p * e + K_i * e_{\text{int}}. \quad (3)$$

Finally, this corrected angular velocity, $\omega_{\text{corrected}}$, is used instead of the raw gyroscope data in the quaternion integration step, effectively applying the corrections. The resulting quaternion is normalized to maintain a unit quaternion, representing the refined orientation estimate. The Mahony filter, thus, acts as a complementary filter, combining short-term gyroscope accuracy with long-term accelerometer and magnetometer stability.

Kalman filtering provides an alternative, statistically optimal framework for sensor fusion [75]. While some studies utilize Kalman filters for IMU and GPS fusion [76], [77], our system relies on the Mahony filter for attitude estimation, and a separate algorithm for the GPS, as described in the Appendix, which provides a robust and accurate estimate of position and orientation. The effects of such fusion can be observed in Fig. 5, showing good agreement on the macroscopic scale.

D. Analysis

Our approach seeks to replace traditional gait analysis and biomechanical modeling, which are typically conducted in specialized laboratory settings using optical motion capture to monitor segments of body movements, with an unsupervised, nondevoted gait monitoring of the patient’s daily activities. The aim is to reduce invasive effects and still maintain reproducibility with a limited level of supervision, as requested by Zhou and Hu [78].

To provide a richer context, preprocessing procedures, implementation of fusion techniques, and ontology referencing

operations must be considered. The concept of ontology, initially rooted in philosophy, has been adapted in computer science as a knowledge artifact that delineates a particular reality and the inherent nature of objects [79]. An ontology can establish a universally accepted lexicon and define (syntactic) guidelines for data representation while also offering a semantic representation of the data. Turcin et al. [80] stated that a domain ontology could be implemented with the process to build a data warehouse architecture to support decisions. Various knowledge domains or disciplines are organized within their respective ontologies, essentially serving as a portrayal of a knowledge realm that contains data, information, and knowledge relevant to that domain. Therefore, the “Ontologie du Systeme Musculo-squelettique des Membres Inferieurs” (OSMMI) [81] has been adopted as the main component of this application, in particular the gait class and its subclasses. However, because of its generic scope, it did not satisfy all the gait requirements, and then, it is needed to integrate different ontologies. To this end, the ontology design patterns (ODPs) will be used for sequence, time interval, and time period, among other relevant concepts, which are modularized and supported by the modular ontology engineering (MOE) methodology [82], [83]. Following this approach, as described in the proposed framework (see Fig. 4), we are ready to move to the modeling layer.

The semantic perspective aims to identify walking periods for PwMS by discriminating different types of activity from the collected data. It will be the first step in the value creation process, and based on it, the quality of gait can be derived, as well as quality evolution based on time. In this way, gait performance can be determined over time on an individual basis. To address this segmentation, the data are automatically partitioned into windows lasting 7 s each, when the data are available and with an overlap of 50%, and the fusion of data between sensors and legs is applied at the signal and feature levels [73]. A Hamming window function is used on each window to minimize data loss between windows and to enhance the signal smoothing of the sensors.

To discern the walking process and considering the susceptibility of PwMS to potential harm, pressure data alone were determined to not provide sufficient reliable information. Consequently, a fusion approach was adopted, integrating data from both the acceleration and gyroscope sensors. An illustrative example of this process is shown in Fig. 6.

The adopted algorithm exploits Parseval’s theorem [84]. Let us denote $x(t)$ as the magnitude of acceleration or gyroscope readings over time, while f is the frequency decomposition of $x(t)$. Since we assume that walking implies an energy consumption over time, let us estimate the energy E of the $x(t)$ signal by

$$E = \int_{-\infty}^{\infty} |x(t)|^2 dt = \int_{-\infty}^{\infty} |\tilde{x}(f)|^2 df \quad (4)$$

where

$$\tilde{x}(f) = \int_{-\infty}^{\infty} x(t) \cdot e^{-2\pi f t} dt. \quad (5)$$



Fig. 6. Spectrogram analysis of walking sequence, where energy concentration near 1 Hz confirms automatic gait detection. This illustrates how frequency-based analysis outperforms simple step counts.

Therefore, the spectral density of the energy is defined as

$$S_x = |\tilde{x}(f)|^2. \quad (6)$$

For signals extending continuously across time intervals, it is more advantageous to characterize the distribution of signal power across frequencies using the PSD. The power of the signal in a given frequency band $[f_1, f_2]$, where $0 < f_1 < f_2$, can be calculated by integrating over frequency. Since $S_x(-f) = S_x(f)$, an equal amount of power can be attributed to positive and negative frequency bands, which is responsible for the factor of two in the following equation:

$$P = \int_{-f_1}^{f_2} S_x(f) df. \quad (7)$$

To analyze how the PSD is changing over the time, we have selected a spectrogram tool because it involves time versus frequency versus amplitude and since we are using predefined time segments convoluted with the Hamming window, larger time effects are dismissed. Therefore, values above a threshold

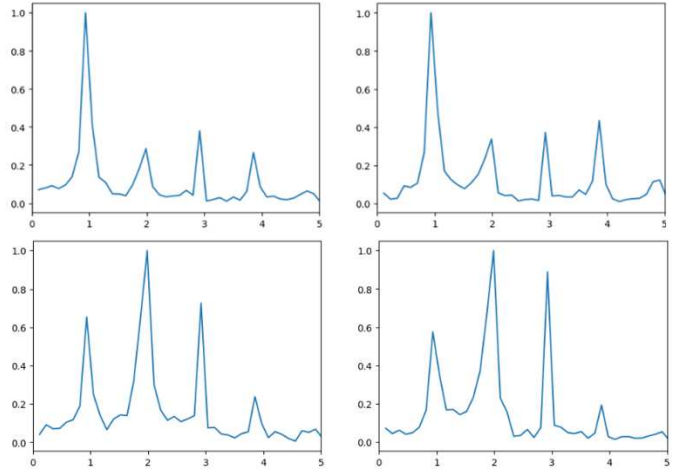


Fig. 7. STFT of a 7-s gait segment. Gyroscope (top) and accelerometer (bottom) signals from right and left legs, showing dominant peak at 1 Hz.

in the amplitude of the PSD with frequencies below 2 Hz are a clear mark in time for walking behavior, as depicted in Fig. 6, bottom. Gait lasting less than 5 s was discarded as the interest is to measure gait power and not just movements involving a few steps but not real walking processes.

Based on the concept of Group 3 information in the DataBase Mechanics Morphology Movement (DB3M) [85], various parameters related to physical measurements have been established. These parameters are defined, and steps are identified specifically for situations that involve walking. In particular, references to the InfluxDB timestamp are maintained within the database.

Using these data with the time windows previously mentioned, the algorithm involving the PSD spectrogram is used to identify gait sequences. It is important to note that, in the context of cyclic activities such as walking, the gyroscope is more sensitive than the accelerometer [86], but contributions from both are needed to increase reliability. Therefore, in this proposal, the gyroscope is significantly relevant and its use is combined with signals from the accelerometer module.

Human walking frequencies typically fall within the 0.6–2-Hz range (equivalent to cycle periods of 1.6–0.5 s) [87]. To accurately capture these frequencies, the Nyquist–Shannon sampling theorem dictates a minimum sampling rate of twice the highest frequency of interest. Consequently, we analyze the frequency band from 0 to 5 Hz, providing a margin above the theoretical minimum of 4 Hz (see Fig. 7). The proposed method enables the identification of walking segments based on the frequency characteristics of the acquired signals. Automatic gait segmentation was validated in a cohort of 35 PwMS with varying degrees of disease progression and 12 healthy control subjects, the combined group representing a diverse range of demographic and anthropometric characteristics. The duration of monitoring for each participant ranged from several hours to two days. These tests have been conducted within the framework of a protocol validated by the Ethics Committee (CEIm) of Getafe University Hospital and have received the necessary informed consent from each participant.

TABLE I

SUMMARY OF THE CNN + LSTM MODEL ARCHITECTURE. IT INVOLVES 198 472 PARAMETERS, 66 050 TRAINABLE, AND 132 102 OPTIMIZER PARAMETERS. THE OPTIMIZATION ALGORITHM SELECTED IS ADAM, THE LEARNING RATE IS 0.0003, AND THE LOSS FUNCTION IS CATEGORICAL CROSS-ENTROPY. THE DROPOUT PARAMETER IS 0.4

Layer (type)	Activation Fun.	Output Shape	Param #
(Conv1D)	ReLU	(None, 206, 32)	608
(MaxPooling1D)		(None, 103, 32)	0
(BatchNormalization)		(None, 103, 32)	128
(Conv1D)	ReLU	(None, 103, 64)	6,208
(MaxPooling1D)		(None, 51, 64)	0
(BatchNormalization)		(None, 51, 64)	256
(Conv1D)	ReLU	(None, 51, 64)	12,352
(MaxPooling1D)		(None, 25, 64)	0
(BatchNormalization)		(None, 25, 64)	256
(LSTM)		(None, 25, 64)	33,024
(Dropout)		(None, 25, 64)	0
(LSTM)		(None, 32)	12,416
(Dropout)		(None, 32)	0
(Dense)	ReLU	(None, 32)	1,056
(Dropout)		(None, 32)	0
(Dense)	SoftMAX	(None, 2)	66

TABLE II

CLASSIFICATION PERFORMANCE OF THE DL MODEL

	Precision	Recall	F1-score	Support
0	0.97	1.00	0.98	23
1	1.00	0.96	0.97	19
Accuracy			0.98	42
Macro avg	0.98	0.97	0.98	42
Weighted avg	0.98	0.98	0.98	42

Complementing the proposed algorithm, the authors implemented a deep learning classifier as an alternative approach, leveraging artificial intelligence (AI) to facilitate semantic segmentation of human movement data, specifically focusing on gait patterns in MS individuals. Since there are six features involved (modulus of acceleration, gyroscope, and magnetometer as well as pressure sensors), a CNN was selected to elaborate on the integrated perspective, as well as an LSTM approach that allows for considering the temporary evolution, with an architecture presented in Table I.

The convolutional kernel size of 3 was selected to detect short-term patterns in gait signals, while max-pooling layers of size 2 were used to reduce temporal resolution and prevent overfitting. A three-layer convolutional stack followed by LSTM units enables a hierarchical extraction of gait features, from low-level signal variations to high-level temporal dependencies.

Performance of the model is presented in Table II, and to increase the interpretability, an attention mechanism was introduced. In this way, detailed information regarding the features retained by the model through time was extracted in terms of the weights of features, and they are discussed in the next paragraph.

The attention weights presented in Fig. 8 show on the X-axis different feature dimensions extracted by the preceding LSTM layer, while on the Y-axis are sequential steps from the time-

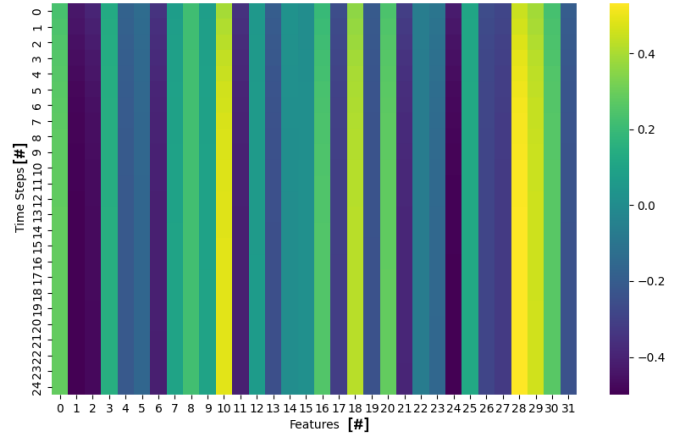


Fig. 8. Attention map of CNN-LSTM model. The model consistently focuses on specific gait-cycle features, confirming that learned representations align with physiologically relevant gait phases.

series data (from smart socks). Brighter colors indicate higher positive attention, which means that the model heavily relies on these particular features, while darker colors mean lower or negative attention for these features, with less emphasis from the model on these features.

We can understand the features as discriminative segments in the gait cycle. The consistent pattern across time steps could indicate stable features that significantly influence the model predictions throughout the sequence. Consequently, the model shows consistency over time since individual samples were either for walking or nonwalking activities.

The model has been trained with four-second data segments, and validation is also performed over four-second signals. Its performance is represented in Fig. 9.

To assess the added value of the deep learning approach with attention mechanisms, a comparative evaluation was performed using support vector machines (SVMs) and random forest classifiers trained on the same dataset and evaluated under the same cross-validation protocol. The average accuracies obtained across the folds were presented in Table III.

Although all three models achieved high accuracy on the full dataset, the performance of the CNN-LSTM-Attention model is justified based on its superior stability and functional design. While the average accuracy of the deep learning model (97.10%) is numerically close to the SVM and random forest classifiers (both at 96.62%), its standard deviation of $\pm 1.18\%$ is significantly lower than that of the SVM ($\pm 3.80\%$) and random forest ($\pm 1.81\%$). This indicates a more stable and reliable model, which is a critical requirement for long-term clinical monitoring. Furthermore, while all models produced similar *F1* scores (0.97), the CNN-LSTM-Attention model provides more interpretability through its attention mechanism (Fig. 8) and is specifically capable of capturing the temporal dependencies inherent in gait sequences, something traditional models like SVM and random forest are not designed to do. This combination of higher stability and richer, time series-specific insight justifies the adoption of a deep learning architecture for this application.

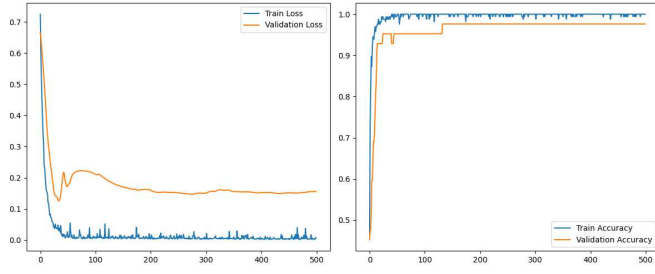


Fig. 9. Performance of the CNN + LSTM model to distinguish gait from other behaviors.

Having achieved automatic gait activity identification in noncontrolled environments, the remaining objective is to identify persistent gait features within those identified periods that reliably correlate with MS disease severity.

The quasi-periodicity of human walking implies that locomotion patterns have repetitive characteristics, although with subtle variations that are the outcome of biomechanical processes. The periodicity suggests that information gathered from the socks, particularly the acceleration and gyroscopic data, had ordered spectral characteristics that may be identified with the application of time–frequency analysis methodologies. As an example for local analysis, a segment of 7 s was chosen from the recorded data presented in Fig. 3, which was further processed with the STFT following normalization and smoothing procedures are presented in Fig. 7. Fig. 10 presents the same analysis for pressure channels 0–2 (located as indicated in Fig. 1).

To make the spectral analysis accurate, the raw signals were subjected to a preprocessing stage that included smoothing and normalization. The normalization process guarantees that all the features are in the same range, making the sensor differences minimal. In addition to normalization, smoothing is used to remove high-frequency noise. This is normally achieved using a low-pass filter, where a moving average filter can be expressed as

$$x_{\text{smooth}}(t) = \frac{1}{N} \sum_{i=0}^{N-1} x(t-i). \quad (8)$$

In this case, the smoothing process ensures that only frequency components below 5 Hz are retained, thus emphasizing the dominant gait dynamics while suppressing unwanted noise.

After preprocessing, the signals are analyzed in the frequency domain using STFT. The STFT shows how different frequency components change over time by calculating the Fourier transform using a sliding window. Mathematically, the STFT of a signal $x(t)$ is

$$X(t, f) = \int_{-\infty}^{\infty} x(\tau) w(\tau - t) e^{-j2\pi f\tau} d\tau \quad (9)$$

where $w(\tau - t)$ represents a window function that isolates a short segment of the signal around t , and $e^{-j2\pi f\tau}$ corresponds to the Fourier basis function.

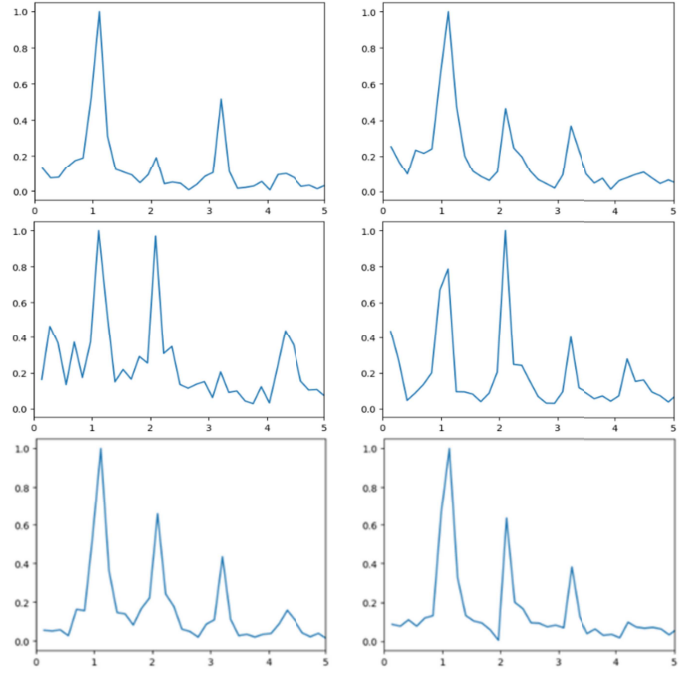


Fig. 10. STFT for gait data lasting 7 s. Rows represent S0–S2 according to the position described in Fig. 1, right. Meaning of columns and axes are the same as that in Fig. 7.

The resulting STFT coefficients $X(t, f)$ describe the distribution of spectral energy over time and frequency. For analysis purposes, the modulus of the STFT is extracted, yielding

$$|X(t, f)| \quad (10)$$

as the time–frequency representation of the signal. By applying STFT to the modulus of both the acceleration and the gyroscope signals from both legs, a comprehensive view of the spectral characteristics of gait is obtained.

The principal frequency observed in the STFT corresponds to the principal frequency of the walking cycle, typically around 1 Hz for a healthy adult. Additional harmonic components may be present due to subtle details in the walking pattern. Examination of the spectral features of the left and right legs provides insight into gait symmetry and variability. Abnormal results in these features can indicate issues in walking mechanics, which can assist in medical diagnosis and rehabilitation procedures.

The detailed analysis of frequencies shows a peak at 1.05 Hz (0.95 s) on both legs, compatible with the sequence of steps presented, and the results are aligned among the gyroscope and accelerometer with the main frequency and principal harmonics, which are more sensitive for the latest. Such frequencies are also compatible with the frequencies of pressure signals, where harmonics are again present as well.

IV. RESULTS

Once the new frequency characteristics have been obtained for the identified gait segments, different behaviors of PwMS can be analyzed. In Fig. 11, we analyze the behavior of a severely affected person with MS (EDDS 5.5), where the

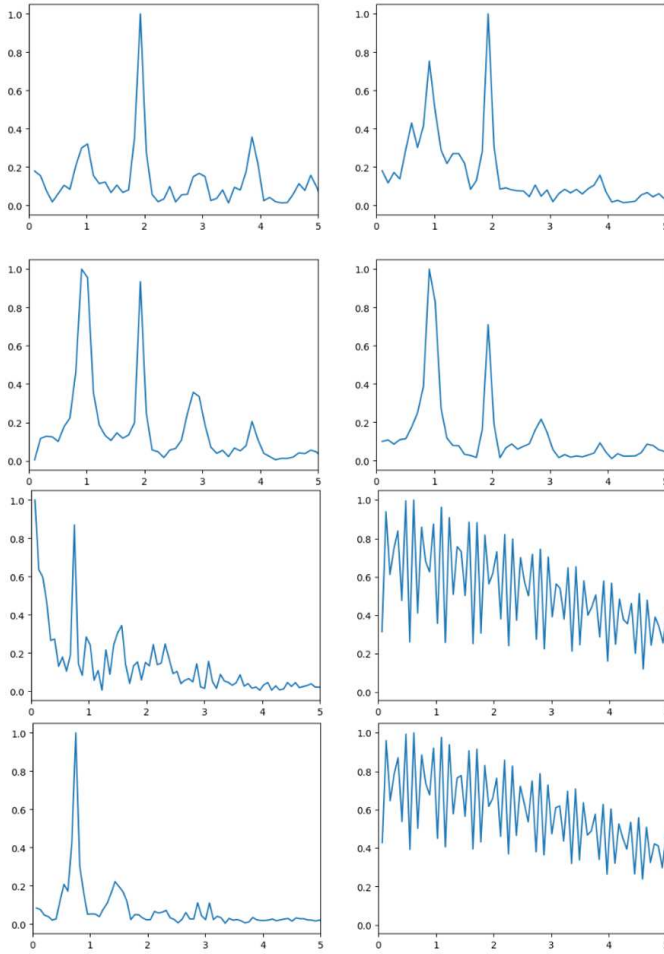


Fig. 11. STFT for gait data of an MS patient with EDSS of 5.5. Rows represent acceleration and gyroscope modulus, S0, and S1, and columns are right and left legs. Other characteristics are the same as those in Fig. 7.

TABLE III

COMPARISON OF AVERAGE CLASSIFICATION ACCURACY (%) AND STANDARD DEVIATION ACROSS MODELS (CROSS-VALIDATION RESULTS)

Model	Average Accuracy	Standard Deviation
CNN-LSTM-Attention	97.10%	$\pm 1.18\%$
SVM	96.62%	$\pm 3.80\%$
Random Forest	96.62%	$\pm 1.81\%$

raw data are the lower Grafana image in Fig. 3, and it is possible to identify a significant modification of the expected response.

Now, it becomes evident that although the behavior of the right leg looks reasonable, it is not the same in the left leg because the frequencies have no structure, and it seems that the foot moves according to its own principles. Closer attention to channel 1 on the right leg shows a significant response at a very low frequency, compatible with the toe of the foot dragged along the ground rather than being lifted and supported with each step. With movement of the left leg, there is a growth in frequencies near 1 Hz, which anticipates the lack of regularity in the behavior of the front part of the feet, as observed for the S0 and S1 channels.

TABLE IV

TOP YODEN'S INDEX VALUES FOR SEVERE MS CLASSIFICATION

Threshold	Sensitivity (TPR)	1 - Specificity (FPR)	Youden's Index
0.840	1.000	0.000	1.000
0.690	1.000	0.231	0.769
0.675	1.000	0.346	0.654
0.615	1.000	0.615	0.385
0.610	1.000	0.731	0.269
0.600	1.000	0.769	0.231
0.960	0.167	0.000	0.167
0.600	1.000	0.846	0.154
0.585	1.000	0.923	0.077
1.960	0.000	0.000	0.000

To establish a preliminary quantitative link between gait spectral characteristics and clinical disability, we conducted an exploratory receiver operating characteristic (ROC) analysis using two key indicators: base frequency and spectral shift derived from pressure and inertial sensor signals. These metrics were aggregated into a composite spectral gait score and evaluated against the EDSS threshold (≥ 5.0 for severe MS). The resulting ROC curve achieved an area under the curve (AUC) of 0.99 (see Fig 12), indicating strong potential discriminatory power of these spectral features in identifying people with severe MS. Using the Youden index, the optimal cutoff point (score = 0.84) yielded 100% sensitivity and 100% specificity within this dataset (see Table IV). These results indicate promising discriminatory power within our dataset; however, it should be interpreted with caution due to the preliminary nature of the study and the limited sample size. These promising results require validation in a larger and more diverse patient cohort to confirm their generalizability.

To further assess the discriminatory power of spectral gait characteristics in clinically relevant categories of disability, EDSS scores were grouped into three strata: mild (EDSS 0–2.5), moderate (EDSS 3.0–4.5), and severe (EDSS ≥ 5.0). This stratification reflects common clinical breakpoints associated with a decrease in functional mobility in PwMS. Using this grouped classification, an ROC analysis was performed to evaluate the ability of spectral characteristics, specifically the base walking frequency and the spectral shift, to differentiate people by severity class.

The adopted pipeline process shows an effective extraction of structural properties that can be connected to the characteristics of the patient. Therefore, the proposed approach brings additional features to be considered in the global assessment of the patient, in particular in the long-term behavior.

For all pairwise comparisons between the severity groups of EDSS—mild versus moderate, mild versus severe, and moderate versus severe—the Youden index reaches its maximum possible value of 1.0. This indicates perfect separation between classes using the spectral gait score.

- 1) For mild versus moderate, the optimal threshold is approximately 0.585, with 100% sensitivity and 0% false positives.
- 2) For both mild versus severe and moderate versus severe, the optimal threshold is around 0.84, also yielding 100% sensitivity and specificity.

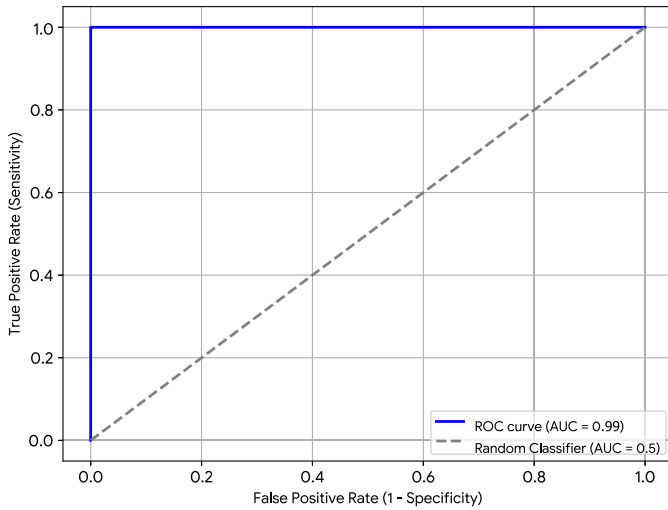


Fig. 12. ROC curve showing that spectral gait features discriminate severe MS (EDSS ≥ 5) with AUC = 0.99. This indicates strong potential as a biomarker for disability stratification.

These preliminary results show that the classifier not only performs well overall (as shown by the AUC of 0.99), but also identifies the optimal decision points with excellent clinical discriminative power in this dataset.

Although these results suggest excellent performance within this dataset, they should be interpreted with caution due to the limited sample size. However, the findings strongly support the potential of spectral gait analysis as a reliable biomarker to stratify MS disability.

V. DISCUSSION

This section is organized into three different components. The first focuses on the main contributions derived from this article. The second explores the limitations, and the last compares the contributions with those carried out in previous works.

A. Main Outcomes

Based on the framework proposed in this article and the specific sensors capable of monitoring gait over time, with the help of the ontological approach adopted, an algorithm for identifying gait has been proposed and tested, which involves the computation of a PSD spectrogram.

The setup choices are made on theoretical grounds and empirical considerations of the literature on gait biomechanics, as well as on preliminary validation carried out on our MS and healthy control datasets, as depicted in Section III. Furthermore, this selected setup enabled successful segmentation of walking epochs and identification of characteristic gait frequency peaks, validated in a cohort of 47 individuals-day dataset. The discriminative performance of the deep learning classifier (CNN + LSTM) further validates the sufficiency of the window and frequency range choices in capturing discriminative gait features. These parameters are also consistent with the literature, such as [20] and [22], which examine the frequency components of gait using wearable IMU sensors.

In this way, the gait of different people with different degrees of MS affectation was analyzed, and the quality of the result is related to the state of MS disability: therefore, the objective of this article, proposing a long-term remote monitoring system for PwMS, is achieved, and new opportunities can be derived. In particular, thanks to the automatic labeling system for gait segments, a potential opportunity can be faced to evaluate the ability of AI transformers to compare gait characteristics and classify the severity of MS disease.

The discriminative performance of the deep learning classifier (CNN + LSTM) further validates the sufficiency of the window and frequency range choices in capturing discriminative gait features, achieving an average accuracy of 97.10% with a low standard deviation of $\pm 1.18\%$. The exploratory ROC analysis for the classification of severe MS also showed a strong potential discriminatory power with an AUC of 0.99.

Using our aggregated spectral gait score, the classifier shows a preliminary good separation between different severity groups within this dataset. For the mild versus moderate comparison, the optimal threshold of 0.585 yielded 100% sensitivity and 100% specificity. Similarly, for both mild versus severe and moderate versus severe, an optimal threshold of 0.84 achieved sensitivity and specificity 100%, reaffirming the clinical discriminative power of our approach.

Although this study focuses on monitoring gait disturbances in real-life situations among PwMS, the underlying principles could be applied to other domains with similar critical factors, such as Parkinson's disease, stroke, and muscular dystrophies [27], [88]. In addition, such analyses can establish a strong basis for managerial and economic research focusing on evaluating the formal implementation of such technologies within clinical practice [89].

B. Limitations

A relevant aspect is the legal anonymization that the collected data can be forced to observe. To enable such observation, the ontology directly connected with the data describes datasets based on the timestamp and mac address of the devices. The connection between these elements and the patient's identity can be made under the secure protocols of the healthcare system used by clinicians, where such information never leaves the secured perimeter.

Following this approach, the analysis tools can later be integrated with supplementary information related to medical prescriptions and historical tracking. However, these aspects have not been considered in this article yet.

More studies are needed to calibrate the rich set of proposed features and fully understand their significance in relation to the impact of MS disability on gait. Given the complexity and variability of MS symptoms, it is crucial to determine how these characteristics behave at different stages of the disease and in response to various external and internal factors.

Of particular interest is the inherent day-to-day variation of gait parameters that needs to be investigated further at the patient level. As is well-appreciated, gait impairments in MS are temporally variable, due in large measure to considerations like fatigue, drug effects, and activity, so reasonable limits of variation must be defined that separate expected fluctuations

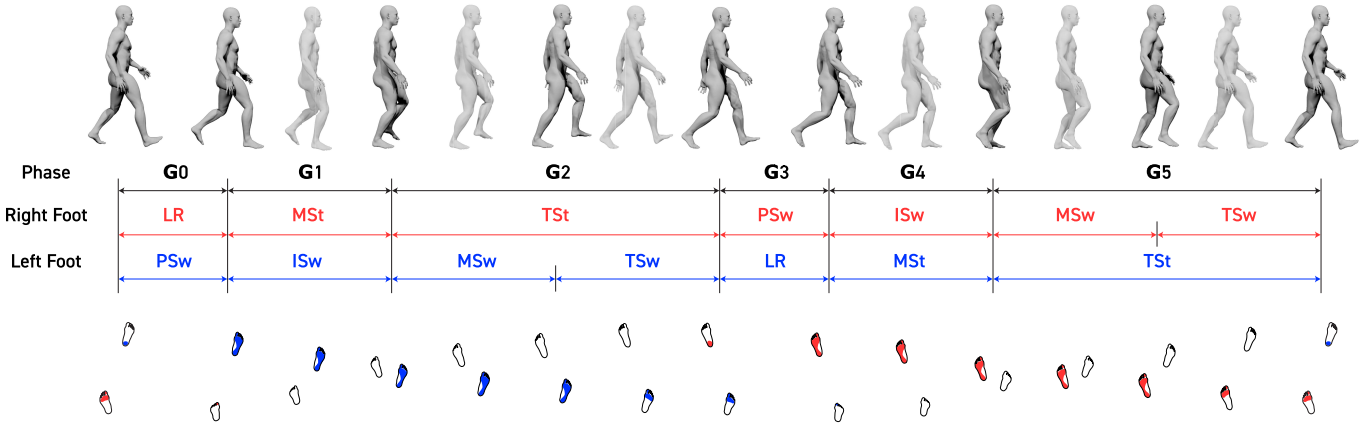


Fig. 13. Full walking cycle, which begins when a foot's heel makes contact with the ground (highlighted point in Fig. 6). The cycle is divided into a stance process and a swing process. The stance process is when the foot is on the ground and consists of three phases. The swing process is when the foot is not in contact with the ground and includes four phases. The figure also shows the adopted phase labeling system, where LR, MSt, TSt, PSw, and ISw are defined as G0–G4, with MSw and TSw combined as G5. The diagram highlights the complementary nature of gait, as one foot is in its stance process while the opposite foot is in its swing process.

from clinically significant changes. A deeper understanding of this intraday variability will be key in the refinement of the practical use of gait metrics in patient monitoring and personalized treatment planning.

Another limitation of this work is the lack of a direct, one-to-one correlation between the traditional gait parameters outlined in Section III-B and the spectral features we analyze. Although our spectral shift and base frequency metrics provide a strong indicator of overall gait quality, a detailed breakdown of individual parameters such as step length and stance time is not the primary output of our current pipeline. However, it is well-established that a lower base frequency in the spectral analysis of gait directly corresponds to a slower gait velocity and a longer stride time, while a broader, less defined spectral peak is indicative of increased gait variability and asymmetry, which are hallmarks of MS-related gait impairment.

A significant limitation of this study is the lack of a direct, quantitative comparison between our proposed spectral gait score and standard clinical measures like the T25FW on the same patient cohort. Such an analysis will be a critical part of our future validation efforts.

Although the system reads sensor data at comparatively high rates (so that it can have fine temporal resolution and fidelity of gait analysis), it is not meant for real-time instantaneous classification or user notification. Rather, sensor data are accumulated locally throughout the day and transmitted in batch mode at a predetermined periodicity (typically nightly, offset for the user's timezone) to a cloud infrastructure for full semantic processing (see Fig. 4). Cloud-based computing is the process of finding time intervals of walking activity, extracting fine-grained gait patterns, scoring local gait characteristics, and producing global analytical summaries that cover a full day or even extended periods (weeks and months). This process allows computationally intensive and clinically valuable analyses to be performed deeply and with accuracy without the constraints of real time. The processed insights are, then, aggregated on a neurologist's dashboard for examination

after daily routine patient screenings. Therefore, conventional latency times for near- or real-time processing are excluded by design because the clinical purpose is for analytical detail and accuracy rather than for rapid reactivity.

In addition, such analyses can establish a strong basis for managerial and economic research focusing on evaluating the formal implementation of such technologies within clinical practice. By quantifying the clinical value of gait analysis in the management of MS, future studies can help validate investments in digital health technology and inform evidence-based decision-making among healthcare professionals, payers, and policy makers. This approach follows from recent attempts to measure the economic and clinical effect of assistive technology, as emphasized in [90].

Finally, successful real-world deployment of the proposed system requires a substantially larger and more diverse patient cohort to ensure the robustness and generalizability of the learning base. To facilitate clinical adoption, the system must also provide intelligent desktop tools that support efficient analysis and interpretation by healthcare professionals. These tools should ensure seamless interoperability with the existing infrastructure and workflows of the health system, allowing for smooth integration into routine clinical practice.

C. Contextual Factors in Gait Analysis

This study's deep learning approach, a CNN-LSTM model with an attention mechanism, demonstrated an average accuracy of 97.10% on our dataset, outperforming a standard SVM and random forest classifier, which both achieved 96.62%. Although the $F1$ scores for all three models were similar (0.97), the lower standard deviation of our model ($\pm 1.18\%$ versus $\pm 3.80\%$ for SVM and $\pm 1.81\%$ for random forest) indicates more stable and reliable predictions. This stability is crucial for long-term clinical monitoring. This performance is competitive with, and in some cases surpasses, similar efforts in the literature for gait analysis in movement disorders. For example, while Sarkar [54] presented a hybrid CNN-LSTM

TABLE V
COMPARISON OF METHODOLOGIES AND INNOVATIONS

Study	Gait Analysis Methodology	Primary Outcome/Metrics	Key Contribution/Innovation
Flachenecker et al. [33]	Wearable sensors (not specified). Focus on gait velocity, cadence, and variability.	Unmasks subtle changes prior to clinical onset.	Demonstrates that wearables can monitor key gait parameters and detect early motor function decline.
Soltani et al. [20]	Wearable inertial sensors.	Close correlation with lab equipment for walking speed and cadence.	Validates wearables for precise gait parameter recording against lab standards.
This Study	Spectral analysis with a deep learning classifier (CNN-LSTM-Attention). A comprehensive semantic framework with ontology for data fusion.	Achieved 97.10% average accuracy and a 0.97 F1-score for gait vs. non-gait classification. Demonstrated a high AUC of 0.99 for severe MS classification.	Remote, continuous, ecologically valid monitoring in real-life settings. Integration of a full semantic IT framework. Superior performance and stability compared to traditional models.

architecture for gait recognition, our model's use of an attention mechanism and its validation on MS-specific data in a free-living context offers a novel and highly effective solution. The ability of our spectral analysis to achieve a 0.99 AUC in distinguishing PwMS provides a powerful, quantifiable metric for clinical decision-making that complements the findings of studies focused on simpler gait metrics.

Furthermore, it is well-established that gait parameters can be affected by cognitive and motor distraction tasks, as shown in research by Kremer et al. [91] and Wajda and Sosnoff [92]. A key consideration in gait analysis using wearable sensors is the influence of external and internal factors on the collected data. Our system addresses this by using instrumented smart socks, which provide a fixed and standardized location for the IMU on the foot, thus minimizing intersubject variability caused by placement differences. Therefore, our remote monitoring approach, which collects data during a patient's natural daily activities, is uniquely positioned to capture these real-world effects. The continuous nature of our data stream, combined with the computational pipeline, allows us to model gait behavior as it is influenced by the patient's natural environment and daily tasks, which is a key advantage over short, in-clinic tests that do not account for these factors. This contributes to a high degree of ecological validity, providing insight into how MS truly affects a person's mobility in their daily life.

D. Comparison With Previous Works

This study develops a feature-based approach that can remotely extract anonymized patient data and match it with the state of MS disability. Adding to the current body of the literature, much of which deals with controlled local trials, this article introduces a new approach that expands step-based features into structural gait characteristics. In addition, its flexible design permits the integration of data from other wearable devices and sensors to enable a complete perspective on automatic gait recognition and MS disability assessment. The incorporation of transformer technology also enhances the capability of the approach, opening up new avenues for innovation in the field, especially after the successful launch of an initial deep learning approach for gait identification.

To contextualize our innovations and objectively highlight our advancements, we provide a structured comparison of this work with other relevant studies in Table V.

Although all three models achieving high accuracy, the CNN-LSTM-Attention model showed slightly superior performance with more stable predictions (as reflected in the lower standard deviation). Although all models produced similar *F1* scores when evaluated in the full dataset (CNN-LSTM-Attention: *F1* score = 0.97, SVM: *F1* score = 0.97, and random forest: *F1* score = 0.97), the CNN-LSTM-Attention model provides more interpretability through its attention mechanism and is capable of capturing the temporal dependencies inherent in gait sequences, something traditional models such as SVM and random forest are not designed to do. This justifies the adoption of a deep learning architecture that is not only competitive in performance but also functionally richer in insight and integration within time series-based pipelines.

This work builds on the foundational contributions of Flachenecker et al. [33] and Soltani et al. [20] by providing a concrete framework for real-world, long-term monitoring, and validating a novel spectral analysis approach with a robust deep learning model. Our results show a powerful and quantifiable metric for clinical decision making, such as the 0.99 AUC of our model to distinguish people with severe MS, which complements the findings of studies focused on simpler gait metrics. The future incorporation of transformer-based AI models will further extend this capability and is a key innovation planned for our pipeline.

In addition, its flexible design allows the integration of data from other wearable devices and sensors to enable a complete perspective on automatic gait recognition and the assessment of MS disability. Incorporation of transformer technology also improves the capability of the approach, opening up new avenues for innovation in the field, especially after the successful launch of an initial deep learning approach for gait identification.

VI. CONCLUSION

This article proposed a method for developing a remote and systematic data collection procedure for MS-related gait disorders based on wearable smart socks. Using a novel

pipeline for data processing and a frequency-based analysis of gait signals, our system addresses the critical shortcomings of conventional clinical evaluations, such as the low sensitivity and reproducibility of the T25FW. The successful deployment of this paradigm of the IoWT demonstrates its potential to go beyond the limitations of single-event, in-clinic tests and provide a more comprehensive and ecologically valid view of patient mobility in their natural environment.

The clinical impact of this approach is substantial and multifaceted. Continuous monitoring enables the early detection of subtle gait changes, guiding more timely interventions. Persistent data streams can support personalized treatment regimens, while noninvasive remote monitoring reduces the need for frequent in-person visits and aligns with emerging telemedicine practices. Importantly, our gait-derived metrics provide clinically meaningful information that current scales, such as the EDSS, fail to capture with sensitivity. The EDSS, while established and widely used, often requires years to reflect a 0.5-point change and may miss early signs of disability progression. Our system demonstrated perfect separation between the mild, moderate, and severe disability groups (AUC = 0.99), suggesting a powerful complementary biomarker for the monitoring of progression. This capability could help avoid the frequent situation in which patients suddenly jump from EDSS 3.0 to 5.5, with years of unrecorded intermediate decline.

From a practical perspective, these metrics help to: 1) assess the impact of MS on real-world daily life, including walking on uneven terrain and open spaces; 2) quantify the rate and manner of progression, particularly in the most debilitating progressive forms of MS where treatments are limited; 3) improve diagnostic accuracy of progression beyond relapses, thus supporting better therapeutic choices; and 4) personalize rehabilitation by targeting the specific gait alterations observed at the step level.

Thus, while our approach is not intended to redefine EDSS, which remains necessary for regulatory and trial purposes, it has the potential to complement it for sensitive longitudinal tracking of MS progression. Ultimately, this work represents a foundational step toward proactive, data-driven, and patient-centric MS management, where subtle mobility changes can be detected earlier, interpreted clinically, and acted upon with tailored interventions.

The proposed method, with its robust gait identification and frequency-based characterization, provided a crucial foundation for building a consistent, labeled dataset. This is a vital step toward creating advanced AI models, including transformer-based architectures, to classify MS disability and even help to make a prognosis of disease progression. Although a larger and more diverse patient cohort is needed to ensure robustness and generalizability, this work represents a significant step toward a new paradigm for patient-centric, data-driven MS treatment.

The proposed method, with additional analyses, is crucial for labeling a consistent set of samples, which will be used to create an AI-based automatic real-time disease classifier using one-day patient data collection sets.

Finally, but importantly, systematic collection of walking records, labeled in a convenient way, can be a source of training advanced AI models, fueled by transformer technology, and able to help make a prognosis on disease progression.

APPENDIX A MATHEMATICS OF MOVEMENT

The analysis has been carried out through quaternion objects. They form a noncommutative division algebra over the real numbers. This means that they satisfy the axioms of a ring (addition, subtraction, and multiplication) and have multiplicative inverses (except for the zero quaternion). Quaternions provide a robust representation of rotations without singularities or gimbal lock [93], [94]. A quaternion q is defined as

$$q = w + xi + yj + zk \quad (11)$$

where w is the scalar component and (x, y, z) are the vector components.

The angular velocity vector $\omega = (\omega_x, \omega_y, \omega_z)$ is converted into a quaternion representation

$$\omega_q = (0, \omega_x, \omega_y, \omega_z). \quad (12)$$

The quaternion derivative is given by

$$\frac{dq}{dt} = \frac{1}{2}q \otimes \omega_q \quad (13)$$

where $\otimes$ represents the multiplication of quaternions. Using numerical integration (e.g., Euler method), the quaternion at time $t + \Delta t$ is updated as

$$q_{t+\Delta t} = q_t + \frac{1}{2}q_t \otimes \omega_q \Delta t. \quad (14)$$

Gyroscopes suffer from drift over time, requiring correction using accelerometer and magnetometer data [95].

The estimated gravity vector from the quaternion is computed as

$$g_{\text{est}} = q_t \otimes (0, 0, 0, 1) \otimes q_t^* \quad (15)$$

where q_t^* is the conjugate of the quaternion. The correction is applied by aligning g_{est} with the measured gravity vector.

The magnetometer provides a heading reference, and the correction is applied via complementary filtering or an extended Kalman filter (EKF) [75].

Once orientation is estimated, acceleration data from the IMU can be used to compute velocity and position.

The acceleration in the global reference frame is obtained by removing gravity

$$a_{\text{global}} = q_t \otimes a_{\text{sensor}} \otimes q_t^* - g \quad (16)$$

where $g = (0, 0, 9.81) \text{ m/s}^2$ is the gravitational acceleration.

Velocity is computed by integrating acceleration over time

$$v_{t+\Delta t} = v_t + a_{\text{global}} \Delta t. \quad (17)$$

To mitigate drift, ZUPTs are used when the IMU is detected to be stationary [77].

Position is computed by integrating velocity

$$p_{t+\Delta t} = p_t + v_t \Delta t + \frac{1}{2}a_{\text{global}} \Delta t^2. \quad (18)$$

The Madgwick filter is unique because it fuses IMU sensors to better estimate orientations over time and minimizes drift error when fuses sensors [47]. Although IMUs provide accuracy in position measurements using dead reckoning when estimating position, they suffer from integration drift, leading to continuous tracking errors. To mitigate position drift, data fusion can help fix it, using GPS fusion with Kalman filtering [76].

The merging of several measurement assets holds great promise for human movement science, such as increased activity recognition and more knowledgeable gait analysis. Wearable and mobile data fusion refers to the integration of multiple sensor modalities to enhance the accuracy, reliability, and scope of real-time monitoring in various applications such as health tracking, motion analysis, and activity recognition. By combining different sensor sources, data fusion mitigates the limitations of individual sensors and provides a more comprehensive understanding of physiological and biomechanical states [67], [96].

APPENDIX B GAIT STRUCTURE

To characterize the gait structure, several relevant features have already been defined and used as reference for the comparative analysis.

1) Temporal Parameters (Timing):

- a) *Stance Time*: Duration (s) of contact between the foot and the ground.
- b) *Swing Time*: Duration (s) of the foot is not in contact with the ground.
- c) *Stride Time*: Duration (s) of one complete gait cycle (one step with each foot).
- d) *Step Time*: Duration (s) between the heel strike of one foot and the heel strike of the opposite foot.
- e) *Double Support Time*: Duration (s) when both feet are in contact with the ground.
- f) *Cadence*: Steps per minute.
- g) *Stance/Swing Ratio*: Ratio of stance time to swing time.
- h) *Stride Time Variability*: Standard deviation of stride times.
- i) *Step Time Variability*: Standard deviation of step times.

2) Spatial Parameters (Distances):

- a) *Step Length*: Distance (m) between successive heel strikes of opposite feet.
- b) *Stride Length*: Distance (m) between successive heel strikes of the same foot.
- c) *Step Width*: Mediolateral distance (m) between the feet during double support.
- d) *Stride Length Variability*: Standard deviation of stride lengths.
- e) *Step Length Variability*: Standard deviation of step lengths.

3) Asymmetry Parameters:

- a) *Step Length Asymmetry*: Step length is a common gait parameter for quantifying gait asymmetry.

b) *Stance time asymmetry*.

c) *Swing time asymmetry*.

4) Variability and Stability Parameters:

- a) *Coefficient of Variation (CV) for Any of the Above Parameters*: $CV = (\text{standard deviation}/\text{mean}) * 100\%$. A higher CV indicates greater variability. Increased variability is a hallmark of MS gait. This can be calculated for stride time, step time, step length, etc.
- b) *Harmonic Ratio*: A measure of gait smoothness.

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REFERENCES

- [1] C. Walton et al., "Rising prevalence of multiple sclerosis worldwide: Insights from the atlas of MS, third edition," *Multiple Sclerosis J.*, vol. 26, no. 14, pp. 1816–1821, Dec. 2020. [Online]. Available: <https://journals.sagepub.com/doi/full/10.1177/1352458520970841>
- [2] A. J. Solomon et al., "Global barriers to the diagnosis of multiple sclerosis," *Neurology*, vol. 101, no. 6, pp. e624–e635, Aug. 2023. [Online]. Available: <https://n.neurology.org/content/101/6/e624.abstract>
- [3] R. Dobson and G. Giovannoni, "Multiple sclerosis—A review," *Eur. J. Neurol.*, vol. 26, no. 1, pp. 27–40, Nov. 2018, doi: [10.1111/ene.13819](https://doi.org/10.1111/ene.13819).
- [4] B. Gbaguidi, F. Guillemin, M. Soudant, M. Debouverie, G. Mathey, and J. Epstein, "Age-period-cohort analysis of the incidence of multiple sclerosis over twenty years in lorraine, France," *Sci. Rep.*, vol. 12, no. 1, p. 1001, Jan. 2022, doi: [10.1038/s41598-022-04836-5](https://doi.org/10.1038/s41598-022-04836-5).
- [5] M. D. Goldman and L. Amezcua, "Progressive multiple sclerosis," *CONTINUUM Lifelong Learn. Neurol.*, vol. 28, no. 4, pp. 1083–1103, 2022. [Online]. Available: https://journals.lww.com/continuum/fulltext/2022/08000/progressive_multiple_sclerosis.8.aspx
- [6] H. Karparkin, B. Siminovich-Blok, J. Rachwani, Z. Langer, and S. Windsor, "Effect of acupuncture on sensorimotor function and mobility in patients with multiple sclerosis: A pilot study," *J. Integrative Complementary Med.*, vol. 29, no. 1, pp. 42–49, Jan. 2023. [Online]. Available: <https://www.liebertpub.com/doi/10.1089/jicm.2022.0610>
- [7] G. Pardo, S. Coates, and D. T. Okuda, "Outcome measures assisting treatment optimization in multiple sclerosis," *J. Neurol.*, vol. 269, no. 3, pp. 1282–1297, Aug. 2021, doi: [10.1007/s00415-021-10674-8](https://doi.org/10.1007/s00415-021-10674-8).
- [8] P. Decavel, T. Moulin, and Y. Sagawa, "Gait tests in multiple sclerosis: Reliability and cut-off values," *Gait Posture*, vol. 67, pp. 37–42, Jan. 2019.
- [9] B. J. Oliver et al., "System-level variation in multiple sclerosis care outcomes: Initial findings from the multiple sclerosis continuous quality improvement research collaborative," *Population Health Manage.*, vol. 25, no. 1, pp. 46–56, Feb. 2022. [Online]. Available: <https://www.liebertpub.com/doi/10.1089/pop.2021.0040>
- [10] S. E. Bennett, L. E. Bromley, N. M. Fisher, M. R. Tomita, and P. Niewczyk, "Validity and reliability of four clinical gait measures in patients with multiple sclerosis," *Int. J. MS Care*, vol. 19, no. 5, pp. 247–252, Sep. 2017.
- [11] R. Phan-Ba et al., "Motor fatigue measurement by distance-induced slow down of walking speed in multiple sclerosis," *PLoS ONE*, vol. 7, no. 4, Apr. 2012, Art. no. e34744.
- [12] R. Phan-Ba et al., "Comparison of the timed 25-foot and the 100-meter walk as performance measures in multiple sclerosis," *Neurorehabilitation Neural Repair*, vol. 25, no. 7, pp. 672–679, Sep. 2011.

- [13] M. D. Goldman, R. W. Motl, J. Scagnelli, J. H. Pula, J. J. Sosnoff, and D. Cadavid, "Clinically meaningful performance benchmarks in MS: Timed 25-foot walk and the real world," *Neurology*, vol. 81, no. 21, pp. 1856–1863, Nov. 2013.
- [14] A. T. Society, "ATS statement: Guidelines for the six-minute walk test," *Amer. J. Respiratory Crit. Care Med.*, vol. 166, no. 1, pp. 111–117, Jul. 2002, doi: [10.1164/ajrccm.166.1.at1102](https://doi.org/10.1164/ajrccm.166.1.at1102).
- [15] D. Brooks and S. Solway, "ATS statement on six-minute walk test," *Amer. J. Respiratory Crit. Care Med.*, vol. 167, no. 9, p. 1287, May 2003, doi: [10.1164/ajrccm.167.9.950](https://doi.org/10.1164/ajrccm.167.9.950).
- [16] American Thoracic Society, "Erratum: ATS statement: Guidelines for the six-minute walk test," *Amer. J. Respiratory Crit. Care Med.*, vol. 193, no. 10, p. 1185, May 2016, doi: [10.1164/rccm.19310erratum](https://doi.org/10.1164/rccm.19310erratum).
- [17] R. Müller, D. Hamacher, S. Hansen, P. Oschmann, and P. M. Keune, "Wearable inertial sensors are highly sensitive in the detection of gait disturbances and fatigue at early stages of multiple sclerosis," *BMC Neurol.*, vol. 21, no. 1, Sep. 2021, doi: [10.1186/s12883-021-02361-y](https://doi.org/10.1186/s12883-021-02361-y).
- [18] G. Di Flumeri, P. Arico, G. Borghini, N. Sciaraffa, A. Di Florio, and F. Babiloni, "The dry revolution: Evaluation of three different EEG dry electrode types in terms of signal spectral features, mental states classification and usability," *Sensors*, vol. 19, no. 6, p. 1365, Mar. 2019, doi: [10.3390/s19061365](https://doi.org/10.3390/s19061365).
- [19] P. W. Tipton, E. R. Stanley, V. Chitu, and Z. K. Wszolek, "Is pre-symptomatic immunosuppression protective in CSF1R-related leukoencephalopathy?" *Movement Disorders*, vol. 36, no. 4, pp. 852–856, Feb. 2021, doi: [10.1002/mds.28515](https://doi.org/10.1002/mds.28515).
- [20] A. Soltani et al., "Algorithms for walking speed estimation using a lower-back-worn inertial sensor: A cross-validation on speed ranges," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 1955–1964, 2021.
- [21] F. B. S. Briggs, N. R. Thompson, and D. S. Conway, "Prognostic factors of disability in relapsing remitting multiple sclerosis," *Multiple Sclerosis Rel. Disorders*, vol. 30, pp. 9–16, May 2019, doi: [10.1016/j.msard.2019.01.045](https://doi.org/10.1016/j.msard.2019.01.045).
- [22] M. Sparaco, L. Lavorgna, R. Conforti, G. Tedeschi, and S. Bonavita, "The role of wearable devices in multiple sclerosis," in *Proc. Multiple Sclerosis Int.*, vol. 2018, 2018, pp. 1–7.
- [23] F. Salaorni, G. Bonardi, F. Schena, M. Tinazzi, and M. Gandolfi, "Wearable devices for gait and posture monitoring via telemedicine in people with movement disorders and multiple sclerosis: A systematic review," *Expert Rev. Med. Devices*, vol. 21, nos. 1–2, pp. 1–20, Feb. 2024. [Online]. Available: <https://pubmed.ncbi.nlm.nih.gov/38124300/>
- [24] B. Bonnechère, "Integrating rehabilitomics into the multi-omics approach in the management of multiple sclerosis: The way for precision medicine?" *Genes*, vol. 14, no. 1, p. 63, Dec. 2022, doi: [10.3390/genes14010063](https://doi.org/10.3390/genes14010063).
- [25] M. A. E.-K. Ahmed, M. F. Zakaria, A. A. E. A. Elaziz, M. M. Fouad, A. M. Elbokl, and M. S. Swelam, "Assessment of the role of telemedicine in the outcome of multiple sclerosis patients," *Egyptian J. Neurol., Psychiatry Neurosurgery*, vol. 59, no. 1, Jul. 2023, doi: [10.1186/s41983-023-00690-y](https://doi.org/10.1186/s41983-023-00690-y).
- [26] M. L. Frechette, B. M. Meyer, L. J. Tulipani, R. D. Gurchiek, R. S. McGinnis, and J. J. Sosnoff, "Next steps in wearable technology and community ambulation in multiple sclerosis," *Current Neurol. Neurosci. Rep.*, vol. 19, no. 10, pp. 1–10, Oct. 2019. [Online]. Available: <https://link.springer.com/article/10.1007/s11910-019-0997-9>
- [27] J. Yeung et al., "Evaluating the sensoria smart socks gait monitoring system for rehabilitation outcomes," *PM R*, vol. 11, no. 5, pp. 512–521, May 2019.
- [28] P. van Oirschot et al., "A two-minute walking test with a smartphone app for persons with multiple sclerosis: Validation study," *JMIR Formative Res.*, vol. 5, no. 11, Nov. 2021, Art. no. e29128. [Online]. Available: <https://formative.jmir.org/2021/11/e29128>
- [29] S. Paluch and S. Tuzovic, "Persuaded self-tracking with wearable technology: Carrot or stick?" *J. Services Marketing*, vol. 33, no. 4, pp. 436–448, Sep. 2019.
- [30] L. Piwek, D. A. Ellis, S. Andrews, and A. Joinson, "The rise of consumer health wearables: Promises and barriers," *PLOS Med.*, vol. 13, no. 2, Feb. 2016, Art. no. e1001953. [Online]. Available: <https://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.1001953>
- [31] D. M. Hilty, C. M. Armstrong, D. D. Luxton, M. T. Gentry, and E. A. Krupinski, "A scoping review of sensors, wearables, and remote monitoring for behavioral health: Uses, outcomes, clinical competencies, and research directions," *J. Technol. Behav. Sci.*, vol. 6, no. 2, pp. 278–313, Mar. 2021. [Online]. Available: <https://link.springer.com/article/10.1007/s41347-021-00199-2>
- [32] A.-C.-L. Leonardsen, C. Hardeland, A. K. Helgesen, and V. A. Grøndahl, "Patient experiences with technology enabled care across health-care settings—A systematic review," *BMC Health Services Res.*, vol. 20, no. 1, pp. 1–17, Dec. 2020. [Online]. Available: <https://link.springer.com/articles/10.1186/s12913-020-05633-4>
- [33] F. Flachenecker et al., "Objective sensor-based gait measures reflect motor impairment in multiple sclerosis patients: Reliability and clinical validation of a wearable sensor device," *Multiple Sclerosis Rel. Disorders*, vol. 39, Apr. 2020, Art. no. 101903. [Online]. Available: <https://pubmed.ncbi.nlm.nih.gov/31927199/>
- [34] J. P. Stellmann et al., "Ecological validity of walking capacity tests in multiple sclerosis," *PLoS ONE*, vol. 10, no. 4, Apr. 2015, Art. no. e0123822. [Online]. Available: <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0123822>
- [35] V. J. Block et al., "Association of continuous assessment of step count by remote monitoring with disability progression among adults with multiple sclerosis," *JAMA Netw. Open*, vol. 2, no. 3, Mar. 2019, Art. no. e190570, doi: [10.1001/jamanetworkopen.2019.0570](https://doi.org/10.1001/jamanetworkopen.2019.0570).
- [36] M. Coca-Tapia, A. Cuesta-Gómez, F. Molina-Rueda, and M. Carratalá-Tejada, "Gait pattern in people with multiple sclerosis: A systematic review," *Diagnostics*, vol. 11, no. 4, p. 584, Mar. 2021.
- [37] M. Psarakis, D. A. Greene, M. H. Cole, S. R. Lord, P. Hoang, and M. Brodie, "Wearable technology reveals gait compensations, unstable walking patterns and fatigue in people with multiple sclerosis," *Physiological Meas.*, vol. 39, no. 7, Jul. 2018, Art. no. 075004, doi: [10.1088/1361-6579/aac0a3](https://doi.org/10.1088/1361-6579/aac0a3).
- [38] G. Abbadessa et al., "Assessment of multiple sclerosis disability progression using a wearable biosensor: A pilot study," *J. Clin. Med.*, vol. 10, no. 6, p. 1160, Mar. 2021, doi: [10.3390/jcm10061160](https://doi.org/10.3390/jcm10061160).
- [39] X. Ferre et al., "Gait speed measurement for elderly patients with risk of frailty," *Mobile Inf. Syst.*, vol. 2017, pp. 1–11, Dec. 2017, doi: [10.1155/2017/1310345](https://doi.org/10.1155/2017/1310345).
- [40] M. Wuehr, A. Huppert, F. Schenkel, J. Decker, K. Jahn, and R. Schniepp, "Independent domains of daily mobility in patients with neurological gait disorders," *J. Neurol.*, vol. 267, no. S1, pp. 292–300, Dec. 2020. [Online]. Available: <https://pubmed.ncbi.nlm.nih.gov/32533324/>
- [41] X. Zheng, A. V. Campos, J. Ordieres-Meré, J. Balseiro, S. L. Marcos, and Y. Aladro, "Continuous monitoring of essential tremor using a portable system based on smartwatch," *Frontiers Neurol.*, vol. 8, Mar. 2017. [Online]. Available: <https://pubmed.ncbi.nlm.nih.gov/28360883/>
- [42] M. Chirra et al., "Telemedicine in neurological disorders: Opportunities and challenges," *Telemedicine e-Health*, vol. 25, no. 7, pp. 541–550, Jul. 2019. [Online]. Available: <https://www.liebertpub.com/doi/10.1089/tmj.2018.0101>
- [43] X. Zheng, A. Vieira, S. L. Marcos, Y. Aladro, and J. Ordieres-Meré, "Activity-aware essential tremor evaluation using deep learning method based on acceleration data," *Parkinsonism Rel. Disorders*, vol. 58, pp. 17–22, Jan. 2019. [Online]. Available: <https://pubmed.ncbi.nlm.nih.gov/30122598/>
- [44] A. Zahn et al., "Validity of an inertial sensor-based system for the assessment of spatio-temporal parameters in people with multiple sclerosis," *Frontiers Neurol.*, vol. 14, Apr. 2023. [Online]. Available: <https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2023.1164001>
- [45] J. C. Perez-Ibarra, A. A. G. Siqueira, and H. I. Krebs, "Identification of gait events in healthy and Parkinson's disease subjects using inertial sensors: A supervised learning approach," *IEEE Sensors J.*, vol. 20, no. 24, pp. 14984–14993, Dec. 2020, doi: [10.1109/JSEN.2020.3011627](https://doi.org/10.1109/JSEN.2020.3011627).
- [46] F.-C. Wang et al., "Detection and classification of stroke gaits by deep neural networks employing inertial measurement units," *Sensors*, vol. 21, no. 5, p. 1864, Mar. 2021, doi: [10.3390/s21051864](https://doi.org/10.3390/s21051864).
- [47] S. A. Ludwig, "Investigation of orientation estimation of multiple IMUs," *Unmanned Syst.*, vol. 9, no. 4, pp. 283–291, Oct. 2020, doi: [10.1142/s2301385021500114](https://doi.org/10.1142/s2301385021500114).
- [48] H. Le and H. Pham, "Learning to estimate critical gait parameters from single-view RGB videos with transformer-based attention network," in *Proc. IEEE Int. Symp. Biomed. Imag. (ISBI)*, May 2024, pp. 1–5.
- [49] H. Dinh, S. Le, M. Than, M. Ho, N. Vuillermé, and H. Pham, "Quantitative gait analysis from single RGB videos using a dual-input transformer-based network," 2025, *arXiv:2501.01689*.
- [50] A. Cosma, A. Catruna, and E. Radoi, "Exploring self-supervised vision transformers for gait recognition in the wild," *Sensors*, vol. 23, no. 5, p. 2680, Mar. 2023.
- [51] D. M. Nguyen, M. Miah, G.-A. Bilodeau, and W. Bouachir, "Transformers for 1D signals in Parkinson's disease detection from gait," in *Proc. 26th Int. Conf. Pattern Recognit. (ICPR)*, Aug. 2022, pp. 5089–5095.

- [52] V. Adeli et al., "GAITGen: Disentangled motion-pathology impaired gait generative model-bringing motion generation to the clinical domain," 2025, *arXiv:2503.22397*.
- [53] N. Basoc, A. Cosma, A. Cătrună, and E. Rădoi, "Database-agnostic gait enrollment using SetTransformers," 2025, *arXiv:2505.02815*.
- [54] M. Sarkar, "Integrating machine learning and deep learning techniques for advanced Alzheimer's disease detection through gait analysis," *J. Bus. Manage. Stud.*, vol. 7, no. 1, pp. 140–147, Jan. 2025.
- [55] P. Kalpana et al., "Explainable AI-driven gait analysis using wearable Internet of Things (Wiot) and human activity recognition," *J. Intell. Syst. Internet Things*, vol. 15, no. 2, pp. 55–75, 2025.
- [56] F. Amitrano, M. Macagno, S. Rossotti, D. Viganò, M. Cesarelli, and G. D'Addio, "E-textile smart socks for gait analysis: A preliminary validation study," *Gait Posture*, vol. 97, p. 26, Oct. 2022.
- [57] J. Ordieres-Meré and R. P. Guillen. (2022). *Ms_tracking*. [Online]. Available: <https://zenodo.org/records/10079192>
- [58] S. N. Z. Naqvi, S. Yfantidou, and E. Zimányi, "Time series databases and influxdb," *Studienarbeit, Université Libre de Bruxelles*, vol. 12, pp. 1–44, 2017.
- [59] A. Farmanesh. (2024). *Developing a Cross-Platform Mobile Application for Health Data Integration and Capture From Multi Devices Using Flutter*. [Online]. Available: <https://oa.upm.es/82457/>
- [60] H. Zhang, X. Liu, J. Li, J. Pan, C. Kiong Loo, and A. Cangelosi, "Research on enhanced gait phase segmentation based on multimodal spatiotemporal information fusion," *IEEE Internet Things J.*, vol. 12, no. 7, pp. 8773–8788, Apr. 2025.
- [61] A. V. Oppenheim, *Discrete-Time Signal Processing*. India: Pearson Education, 1999.
- [62] A. Salarian et al., "Gait assessment in Parkinson's disease: Toward an ambulatory system for long-term monitoring," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 8, pp. 1434–1443, Aug. 2004.
- [63] J. Taborri, E. Palermo, S. Rossi, and P. Cappa, "Gait partitioning methods: A systematic review," *Sensors*, vol. 16, no. 1, p. 66, Jan. 2016.
- [64] D. A. Winter, *Biomechanics and Motor Control of Human Gait: Normal, Elderly and Pathological*. Waterloo, ON, USA: Waterloo Biomechanics, 1991.
- [65] I. Natgunanathan, N. Fernando, S. W. Loke, and C. Weerasuriya, "Bluetooth low energy mesh: Applications, considerations and current state-of-the-art," *Sensors*, vol. 23, no. 4, p. 1826, Feb. 2023, doi: [10.3390/s23041826](https://doi.org/10.3390/s23041826).
- [66] N.-N. Dao, "Internet of Wearable Things: Advancements and benefits from 6G technologies," *Future Gener. Comput. Syst.*, vol. 138, pp. 172–184, Jan. 2023, doi: [10.1016/j.future.2022.07.006](https://doi.org/10.1016/j.future.2022.07.006).
- [67] J. Wang et al., "Seamless indoor-outdoor foot-mounted inertial pedestrian positioning system enhanced by smartphone PPP/3-D map/barometer," *IEEE Internet Things J.*, vol. 11, no. 7, pp. 13051–13069, Apr. 2024.
- [68] I. Voigt, H. Inojosa, A. Dillenseger, R. Haase, K. Akgün, and T. Ziemssen, "Digital twins for multiple sclerosis," *Frontiers Immunology*, vol. 12, May 2021, Art. no. 669811.
- [69] Y. Huang, "Incorporating domain ontology information into clustering in heterogeneous networks," *WIREs Data Mining Knowl. Discovery*, vol. 11, no. 4, May 2021, doi: [10.1002/widm.1413](https://doi.org/10.1002/widm.1413).
- [70] M. Zdravkovic and M. Trajanovic, "Integrated product ontologies for inter-organizational networks," *Comput. Sci. Inf. Syst.*, vol. 6, no. 2, pp. 29–46, 2009, doi: [10.2298/csis0902029z](https://doi.org/10.2298/csis0902029z).
- [71] S. Pouriyeh et al., "Ontology summarization: Graph-based methods and beyond," *Int. J. Semantic Comput.*, vol. 13, no. 2, pp. 259–283, Jun. 2019, doi: [10.1142/s1793351x19300012](https://doi.org/10.1142/s1793351x19300012).
- [72] Z. Z. M. Kassas, M. Maaref, J. J. Morales, J. J. Khalife, and K. Shamei, "Robust vehicular localization and map matching in urban environments through IMU, GNSS, and cellular signals," *IEEE Intell. Transp. Syst. Mag.*, vol. 12, no. 3, pp. 36–52, Fall. 2020.
- [73] R. C. King, E. Villeneuve, R. J. White, R. S. Sherratt, W. Holderbaum, and W. S. Harwin, "Application of data fusion techniques and technologies for wearable health monitoring," *Med. Eng. Phys.*, vol. 42, pp. 1–12, Apr. 2017.
- [74] Y. Liu, T. Cai, H. Yang, C. Liu, J. Song, and M. Yu, "The pedestrian integrated navigation system with micro IMU/GPS/magnetometer/barometric altimeter," *Gyroscopy Navigat.*, vol. 7, no. 1, pp. 29–38, Jan. 2016.
- [75] H. Gu, C. Jin, H. Yuan, and Y. Chen, "Design and implementation of attitude and heading reference system with extended Kalman filter based on MEMS multi-sensor fusion," *Int. J. Uncertainty, Fuzziness Knowl.-Based Syst.*, vol. 29, no. Supp01, pp. 157–180, Mar. 2021, doi: [10.1142/s0218488521400092](https://doi.org/10.1142/s0218488521400092).
- [76] W. Pi et al., "Malicious user detection for cooperative mobility tracking in autonomous driving," *IEEE Internet Things J.*, vol. 7, no. 6, pp. 4922–4936, Jun. 2020.
- [77] Y. Yu et al., "A novel 3-D indoor localization algorithm based on BLE and multiple sensors," *IEEE Internet Things J.*, vol. 8, no. 11, pp. 9359–9372, Jun. 2021.
- [78] H. Zhou and H. Hu, "Human motion tracking for rehabilitation—A survey," *Biomed. Signal Process. Control*, vol. 3, no. 1, pp. 1–18, Jan. 2008.
- [79] A. F. Sawsaa and J. Lu, "A generic model of ontology to visualize information science domain (OIS)," in *Ontologies and Big Data Considerations for Effective Intelligence*. Hershey, PA, USA: IGI Global, 2017, pp. 435–442, doi: [10.4018/978-1-5225-2058-0.ch010](https://doi.org/10.4018/978-1-5225-2058-0.ch010). [Online]. Available: <http://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/978-1-5225-2058-0>
- [80] I. Turcin, V. Ergovic, and M. Lackovic, "Ontology driven decision support system architecture for gait analysis," in *Proc. IFMBE*. Cham, Switzerland: Springer, 2012, pp. 78–81. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-642-34197-7_20
- [81] T.-T. Dao, F. Marin, and M. C. H. B. Tho, "Ontology of the musculo-skeletal system of the lower limbs," in *Proc. 29th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2007, pp. 386–389, doi: [10.1109/IEMBS.2007.4352305](https://doi.org/10.1109/IEMBS.2007.4352305).
- [82] C. Shimizu, P. Hitzler, and A. A. Krisnadhi, "Modular ontology modeling: A tutorial," in *Applications and Practices in Ontology Design, Extraction, and Reasoning*. Clifton, VA, USA: IOS Press, 2020, p. 3, doi: [10.3233/SSW200032](https://doi.org/10.3233/SSW200032). [Online]. Available: <https://shorturl.at/BLuRi>
- [83] T. Marthinus and O. Daramola, "On domain ontology for decision support in the treatment of gait-related diseases," in *Proc. 21st Int. Conf. Comput. Sci. Its Appl. (ICCSA)*, Sep. 2021, pp. 195–203.
- [84] M. Hassanzadeh and B. Shahrrava, "Linear version of Parseval's theorem," *IEEE Access*, vol. 10, pp. 27230–27241, 2022, doi: [10.1109/ACCESS.2022.3157736](https://doi.org/10.1109/ACCESS.2022.3157736).
- [85] T. T. Dao, F. Marin, and M. H. B. Tho, "Predictive mathematical models based on data mining methods of the pathologies of the lower limbs," in *Proc. IFMBE*, vol. 22. Cham, Switzerland: Springer, May 2009, pp. 1803–1807. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-540-89208-3_430
- [86] G. Qi and B. Huang, "Walking detection using the gyroscope of an unconstrained smartphone," in *Proc. Commun. Netw.* Cham, Switzerland: Springer, 2017, pp. 539–548. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-319-66628-0_51
- [87] M. Henriksen, H. Lund, R. Moe-Nilssen, H. Bliddal, and B. Danneskiold-Samsøe, "Test-retest reliability of trunk accelerometric gait analysis," *Gait Posture*, vol. 19, no. 3, pp. 288–297, Jun. 2004.
- [88] J. Jung, W. Choi, and S. Lee, "Immediate augmented real-time forefoot weight bearing using visual feedback improves gait symmetry in chronic stroke," *Technol. Health Care*, vol. 28, no. 6, pp. 733–741, Nov. 2020.
- [89] M. Grijalvo et al., "Sufficiency for PSS tracking gait disorders in multiple sclerosis: A managerial perspective," *Heliyon*, vol. 10, no. 9, May 2024, Art. no. e30001, doi: [10.1016/j.heliyon.2024.e30001](https://doi.org/10.1016/j.heliyon.2024.e30001).
- [90] E. Walter et al., "Cost-effectiveness of the floodlight MS app in Austria. Unlocking the mystery of costs and outcomes of a digital health application for patients with multiple sclerosis," *Digit. HEALTH*, vol. 11, Jan. 2025, doi: [10.1177/20552076251314550](https://doi.org/10.1177/20552076251314550).
- [91] L. Kremer et al., "Cognitive-motor interference in multiple sclerosis revisited: A dual-task paradigm using wearable inertial sensors and the paced auditory serial addition test," *Frontiers Neurol.*, vol. 16, Mar. 2025. [Online]. Available: <https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2025.1546183>
- [92] D. A. Wajda and J. J. Sosnoff, "Cognitive-motor interference in multiple sclerosis: A systematic review of evidence, correlates, and consequences," *BioMed Res. Int.*, vol. 2015, pp. 1–8, Mar. 2015, doi: [10.1155/2015/720856](https://doi.org/10.1155/2015/720856).
- [93] J. K. Lee and W. C. Jung, "Quaternion-based local frame alignment between an inertial measurement unit and a motion capture system," *Sensors*, vol. 18, no. 11, p. 4003, Nov. 2018, doi: [10.3390/s18114003](https://doi.org/10.3390/s18114003).
- [94] Y. Duan, X. Zhang, and Z. Li, "A new quaternion-based Kalman filter for human body motion tracking using the second estimator of the optimal quaternion algorithm and the joint angle constraint method with inertial and magnetic sensors," *Sensors*, vol. 20, no. 21, p. 6018, Oct. 2020, doi: [10.3390/s20216018](https://doi.org/10.3390/s20216018).
- [95] S. Mansoor, U. I. Bhatti, A. I. Bhatti, and S. M. D. Ali, "Improved attitude determination by compensation of gyroscopic drift by use of accelerometers and magnetometers," *Measurement*, vol. 131, pp. 582–589, Jan. 2019, doi: [10.1016/j.measurement.2018.08.067](https://doi.org/10.1016/j.measurement.2018.08.067).

- [96] C. Virginia Anikwe et al., "Mobile and wearable sensors for data-driven health monitoring system: State-of-the-art and future prospect," *Expert Syst. Appl.*, vol. 202, Sep. 2022, Art. no. 117362, doi: [10.1016/j.eswa.2022.117362](https://doi.org/10.1016/j.eswa.2022.117362).



Joaquín Ordieres-Meré (Senior Member, IEEE) received the Ph.D. degree in industrial engineering from the Universidad Nacional de Educación a Distancia (UNED), Madrid, Spain, in 1987.

He was a Full Professor of industrial management with the Universidad de la Rioja, in 1997, and has been with the Universidad Politécnica de Madrid, Madrid, since October 2008. He was involved in over 70 research projects, most of which are international and competitive. He has published more than 150 research articles, with accumulated citations of over 7700. His research interests are related to business analytics. In particular, he focuses on modeling processes from data to improve knowledge and optimize them.

Dr. Ordieres-Meré participates in ISO TC groups and serves regularly as a Reviewer for different journals, including the Editorial Board Membership in few more, such as *Sensors* (MDPI), the *International Journal of Data Mining, Modelling and Management*, and *Frontiers in Built Environment*. He also represents his country as a member of some European Union expert committees such as RFCS TGA5.



Mercedes Grijalvo received the Ph.D. degree in mechanical engineering and industrial organization from the Charles III University of Madrid, in 2009.

She was an Associate Professor of industrial management with the Charles III University of Madrid, in 2009, and has been with the Universidad Politécnica de Madrid, Madrid, Spain, since September 2011. She has also been a Visiting Professor with the Centre de Recherche en Gestion de l'École Polytechnique, Paris, France, and Southern Illinois University, Carbondale, IL, USA. Finally, in the last years, she had served at different leading positions in the board of the department, involving more than 130 members, as well as in different secretaries of different Ph.D. and master's programs. She has authored or co-authored more than 50 publications, including articles, books, and book chapters, of which 30 are in scientific publications indexed in JCR and SJR, and 20 in Q1 and Q2 journals. Her research interests include innovation and digitalization, both from a business and an educational perspective.

Dr. Grijalvo serves regularly as a Reviewer for international journals, such as the *Journal of Business Research* and *Technological Forecasting and Social Change*. Highlight her experience in participating in research projects, both in competitive calls from several organizations such as the ones developed with companies.



Guillermo Martín-Ávila received the degree in medicine from the Universidad Autónoma de Madrid, Madrid, Spain, in 2016, and the degree in neurology from the Hospital Universitario de Getafe, Getafe, Madrid, in 2021.

He is a member of the Research Group, Multiple Sclerosis Unit (MS Unit), Hospital Universitario de Getafe, whose director is Dr. Aladro as Group 79 of IdiPAZ. With this research group, he participates in several clinical studies pending completion among which are the study on biosensors applied in medicine and which includes the School of Industrial Engineers, Polytechnic University of Madrid. This group initially worked with biosensors in essential tremor and is currently in the analysis of gait in people with MS (PwMS). He is an active collaborating researcher in other projects under development with the MS Unit.



Yolanda Aladro received the degree in medicine from the Universidad Autónoma de Madrid, Madrid, Spain, in 1981, the degree in neurology from the Hospital San Carlos de Madrid, in 1986, and the Ph.D. degree from the Universidad Europea de Madrid, in 2023.

She worked with the Hospital Universitario Dr Negrín, Las Palmas de Gran Canaria, Spain, and also with the Hospital Universitario de Getafe, Madrid, since 1986 and in the field of multiple sclerosis (MS) and other demyelinating diseases since 1991. She is the Coordinator of the MS Unit, University Hospital of Getafe, Getafe, Madrid, and also a Professor of neurology with the Universidad Europea de Madrid. She is an expert in MS, to which she has been dedicated for more than 30 years, both in the field of care and research, and heads the Research Group 79, which focuses on clinical research in MS. She has 106 indexed publications, 2263 citations, and an H index of 17 according to the Web of Science.

Dr. Aladro is a Research Member of Spanish MS Network (REEM), the Vice President of the Medical Advisory Board (MAB) of Spanish MS Association, and a member of the MAB of MS Spain. She is a member of the Study Group of Demyelinating Diseases (SGDD) of Spanish Society of Neurology and a Coordinator of the SGDD of Madrid Association of Neurology.