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RESEARCH ARTICLE

Evaluation of Gait Disorders Using Accelerometric and Gyroscopic Data for Assessment of Neurological Diseases

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ABSTRACT Computational intelligence and digital signal processing are essential mathematical tools widely applied in biomedical and engineering domains. Gait symmetry analysis is particularly important for detecting motion disorders in neurology, rehabilitation, and sports science. This study presents a methodology for motion analysis using time-synchronized accelerometric and gyrometric sensors to capture dynamic gait patterns. Data were collected from 14 healthy controls and 17 individuals with Parkinson's disease-related gait impairments. The proposed approach integrates spectral analysis and digital filtering to remove noise and irrelevant frequency components during signal preprocessing. Motion classification is performed by analyzing energy distribution using discrete Fourier and wavelet transforms, enabling multilevel signal decomposition. Gait recognition—distinguishing between normal and abnormal patterns—is based on energy components in selected frequency bands and their ratios. Neural network classifiers achieved the highest performance, with a mean accuracy of 81.1% and a cross-validation error of 0.123, using data from sensors placed on the left and right sides of the body. Motion asymmetry detected by the model agreed with assessments of neurologists in 88% of cases. Results of this validation highlight the potential of frequency and scale domain analysis, digital signal processing, and artificial intelligence use in supporting the clinical diagnosis of Parkinson's disease and further neurological disorders.

INDEX TERMS Gait analysis, stroke, Parkinson's disease, computational intelligence, signal processing, balance function, wireless sensors, accelerometers, gyrometers, rehabilitation, physical activity monitoring.

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I. INTRODUCTION

Gait is one of the most sensitive motor outputs affected by both neurological and orthopaedic diseases. Wearable inertial measurement units (IMUs) allow unobtrusive, longitudinal monitoring of spatiotemporal parameters and joint kinematics in clinic and home settings. Expressing these signals through symmetry oriented metrics (e.g., ratio, difference or phase planar approaches) provides a compact, noise robust descriptor of inter limb coordination that is highly responsive to both disease progression and therapeutic change.

Walking is a highly complex biomechanical process involving coordinated movements across multiple joints and muscle groups. The intricacy of human locomotion has intrigued scholars since antiquity. One of the earliest recorded efforts to study gait comes from the Greek philosopher Aristotle (384–322 BCE), who is often regarded as the founder of biomechanics. The interest in motion appeared in a large scale also in Renaissance, when figures such as Leonardo da Vinci (1452–1519) and Giovanni Alfonso Borelli (1608–1679) revisited biomechanics with a more scientific approach. Borelli, often considered the father of modern biomechanics, analyzed the forces involved in walking and running, integrating anatomical knowledge with the principles of physics. The modern era of gait analysis began in the late 19th century with the development of motion photography. Latest technological advances allowed for more sophisticated gait analysis, incorporating electromyography (EMG), and motion capture systems. Today, wearable sensors, including accelerometers and gyroscopes, enable real-world motion monitoring. Gait patterns are now recognized as important biomarkers for diagnosing and monitoring a range of neurodegenerative disorders, such as Parkinson's disease, multiple sclerosis, and stroke-related impairments.

The rapid advancement of sensor technology [1], [2] has provided valuable data sources for gait analysis [3], [4], detection of biomarkers [5], [6], and monitoring of rehabilitation progress [7]. Sensors are typically placed on the legs, arms, lower back, or chest to capture comprehensive motion data. Numerous studies describe Micro-electro-mechanical-sensors (MEMS) [8], [9], [10], [11], laser-based LiDAR, and global navigation satellite systems (GNSS) [12], [13] for tracking walking routes. The integration of these advanced technologies presents significant opportunities to improve early diagnosis and personalized treatment of motion-related disorders.

Across a spectrum of neurological and orthopaedic disorders, IMU studies have demonstrated that deviations from left–right symmetry constitute an early and sensitive biomarker. In Parkinson's disease (PD) [7], [14], [15], stride length, stance time and arm swing asymmetries extracted from shank and wrist mounted sensors correlate strongly with clinical severity [16]. A sensor based "semiogram" in multiple sclerosis captures fatigability driven changes in gait symmetry over months, outperforming conventional disability scores [17], [18], [19]. Longitudinal IMU monitoring after stroke reveals a characteristic trajectory from pronounced stance time asymmetry toward balanced loading during rehabilitation, information that can guide adaptive exoskeleton control [20]. Patient specific asymmetry profiles derived from short walking bouts are highly reliable in incomplete spinal cord injury, supporting their use as remote outcome measures for locomotor training [6], [21], [22].

Even in slowly progressive ataxic disorders [23], symmetry based metrics detect clinically meaningful change within one year—well before standard scales—highlighting their utility as surrogate endpoints [24]. Beyond the nervous system, wearable sensors quantify asymmetry in unilateral or painful conditions: arm swing deviation mirrors lower limb deficits in spastic cerebral palsy [25], single sensor symmetry indices discriminate diabetic peripheral neuropathy from healthy gait [26], and stance time or trunk lean asymmetries sensitively track pain induced adaptations in knee osteoarthritis [27]. Collectively, these findings underscore the disease agnostic nature of symmetry focused IMU analysis and its suitability for unsupervised deployment in real world environments.

Recent studies have confirmed that dominant accelerometric frequency components differ significantly between individuals with normal gait and those with PD. Individuals with PD typically exhibit lower dominant frequencies, a consequence of slower walking speeds and shorter stride lengths. Moreover, PD gait is often marked by increased variability and irregular timing, which results in broader or multiple peaks within the frequency spectrum.

Digital signal processing (DSP) techniques, computational techniques, and artificial intelligence (AI) provide mathematical frameworks integrating different disciplines of engineering and biomedicine [28], [29]. Mathematical tools include the discrete Fourier transforms, wavelet-based signal decomposition [30], [31], [32], and machine learning in data classification [33], [34], [35]. These techniques support the recognition of walking patterns [36], [37], monitoring of motion asymmetry, tremor detection [38], and monitoring of cardiovascular diseases [39], [40], [41], [42].

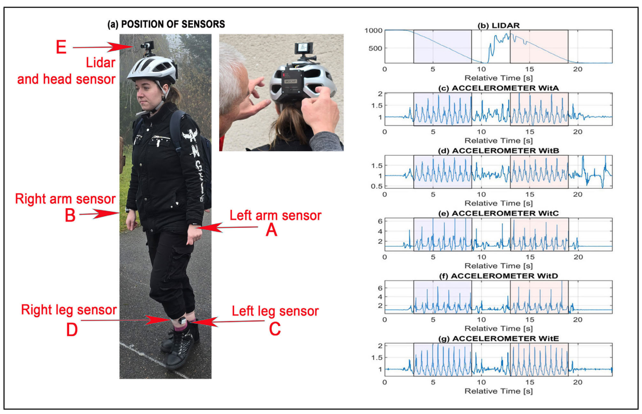

FIGURE 1. Principle of data acquisition presenting (a) body position of sensors, (b) distance [cm] recorded by LiDAR, (c-g) accelerometric signals [m/s^2] acquired by accelerometers for walking in the first (blue-part) and the second (red-part) walking segment.

This paper investigates the use of wearable accelerometers [23] to analyze gait symmetry through the deployment of multisensor systems and evaluation of data in both spectral and scale domains. Wearable sensors were placed on the upper and lower limbs, as illustrated in Fig. 1, enabling comprehensive data acquisition. The primary aim is to demonstrate how walking patterns can be continuously monitored, their symmetry quantitatively assessed, and gait disorders reliably detected. This approach offers neurologists an integrated framework for gait analysis across spectral and spatial dimensions.

The specific objectives of the study include (i) the acquisition of synchronized accelerometric and gyroscopic data from subjects exhibiting normal and abnormal gait patterns, (ii) the extraction of motion features in both frequency and scale domains, (iii) the classification of gait symmetry based on clinical labeling by experienced neurologists, and (iv) the application of AI to detect early signs of gait impairment and assist clinical decision-making [15], [43], [44]. The novelty of this paper lies in combining multi-sensor synchronized accelerometric and gyroscopic data with both frequency- and scale-domain features, and validation of results against clinical scores.

II. METHOD

A. DATA ACQUISITION

Figure 1 illustrates the principle of data acquisition and provides sample signals recorded during forward and backward walking. Four accelerometric sensors WitMotion WIT901BLECL5.0 were placed on the left and right sides of the body, positioned on the wrists and ankles. To ensure the reproducibility of experiments, accelerometric sensors were attached with the elastic straps about 5cm above the ankles and wrists with y-axis pointing up. The time synchronization of all sensors was done by the chip time associated with all acquired data values. Recorded acceleration and angular velocity data are saved as CSV files, which were later converted into XLSX tables for further processing.

An additional accelerometric sensor was mounted on a helmet, integrated with a LiDAR system to measure the distance between the walking individual and the wall in front of him. Local memory was used in the present version of the system to record observed multichannel signals. The data were sampled at a frequency of 200 Hz.

Table 1 presents details of two sets of subjects with the normal and abnormal gait used for motion analysis. They include 14 normal and 17 abnormal subjects diagnosed by experienced specialists. All evaluated patients were assessed with the NIH (National Institute of Health) Stroke Scale (NIHSS) at the time of admission to the rehabilitation department. Those scoring more than 7 points on the NIHSS, indicating moderate to severe stroke [45], were assigned to the stroke group.

All procedures involving human participants complied with the ethical standards of the institutional research committee and adhered to the 1964 Helsinki Declaration and its subsequent amendments. Detailed descriptions of the observations can be found on IEEE DataPort (doi: 10.21227/rh5k-k445, Motion Data for Gait Analysis) for further investigation. This repository contains signals used in the present study and a graphical video abstract.

TABLE 1. Description of the set of individual with normal and abnormal gait presenting the mean age and standard deviation (*STD*) in separate sets.

Set	*Number of Individuals*			*Statistics*	
	Total	*Males*	*Females*	*Mean age*	*STD*
Normal	14	8	6	48.4	12.7
Abnormal	17	9	8	65.7	17.1

B. SIGNAL PROCESSING

Accelerometric and gyrometric data for each experiment were recorded by tri-axial sensors positioned on the left and right leg and arm. Each of this sensor generated three sequences $\{s_x(n), s_y(n), s_z(n)\}_{n=0}^{N-1}$ with their modulus calculated by the following relation:

$$s(n) = \sqrt{s_x(n)^2 + s_y(n)^2 + s_z(n)^2} \tag{1}$$

for $n = 0, 1, \cdots, N-1$. These signals were preprocessed by the low pass FIR filter of order $M = 20$ and normalized cutoff frequency $f_c = 0.2$. The following analysis was performed both in the spectral domain using the discrete Fourier transform (DFT) and in the scale domain using the discrete wavelet transform (DWT).

The DFT was applied to evaluate:

$$S(k) = \sum_{n=0}^{N-1} (s(n) - \bar{s})\, e^{-j\,k\,n\,2\,\pi/N} \tag{2}$$

for $k = 0, 1, \cdots, N-1$ and $\bar{s}$ standing for signal mean value. The single harmonic function of the indefinite length is used here as a core element for this functional transform. The use of spectral-domain features required the evaluation of the relative power E_p for each data segment d and sensor position p in two frequency bands $FB1 = \langle fc_1, fc_2 \rangle$ and $FB2 = \langle fc_3, fc_4 \rangle$:

$$E_p(d) = \frac{\sum_{k\in\Phi_w} |S(k)|^2}{\sum_{k=0}^{N/2} |S(k)|^2} \tag{3}$$

where Φ_w represents the set of indices for the frequency components f_k within each of selected frequency ranges. The frequency-domain features include relative power within the same frequency bands, chosen individually for both the left and right legs and arms.

In each experiment, two time-domain sections were selected, and for each of them, the relative energy in two frequency bands, $FB1$ and $FB2$, were calculated for evaluation of features and estimation of walking symmetry.

While Fourier analysis provides precise frequency decomposition but lacks temporal resolution, the DWT enables multi-resolution time-scale analysis. By combining both, we capture stable frequency-domain asymmetries and transient gait irregularities. The mother wavelet function is dilated and translated to form a framework for analyzing signals at different scales that enable both a global view and a detailed examination of local signal properties.

The symmetry index, calculated using a widely adopted methodology, quantifies the similarity between the left and right sides of the body for each data segment d. It is defined as:

$$C1(d) = \frac{|F_L(d) - F_R(d)|}{0.5\,(F_L(d) + F_R(d))}\,100 \tag{4}$$

Here, $F_L(d)$ and $F_R(d)$ represent signal features estimated for the left and right sides, respectively. These calculations were done for accelerometric and gyrometric signals acquired on legs and arms using both DFT and DWT features.

Feature values associated with the left and right sides of the body were then used for the construction of the pattern matrix

$$\mathbf{P}_{R,Q} = \begin{bmatrix} E_{Left}(d) \\ E_{Right}(d) \end{bmatrix} \tag{5}$$

of Q segments and each its column associated with the individual having normal or abnormal gait in the selected segment d. The target vector $\mathbf{T}_{1,Q}$ contains the specification of class $C1$ or $C2$ that is associated with each feature column vector of matrix $\mathbf{P}_{R,Q}$ specified by an experienced neurologist and standing for normal and abnormal gait, respectively.

During the learning process, the mathematical model that transforms the space of features $\mathbf{P}_{R,Q}$ into the vector $\mathbf{T}_{1,Q}$ specifying the classes, is estimated. Results of classification using the nearest neighbour, Bayesian, and support vector machines methods were compared with those obtained by neural networks. The present study is based on their simple two-layer structure with 2 input neurons, 10 neurons in their first layer with a sigmoidal transfer function, and two neurons with a probabilistic transfer function in the final layer. Optimization coefficients included the selection of the learning rate 0.001, 400 iterations, and Adam optimizer.

Verification was done by the evaluation of the k-fold cross validation method and statistical testing of individual models based on the record of accuracy for each folder. The mean accuracy was then computed. Associated 95% confidence intervals were estimated using a t-distribution. The paired t-test on the fold-wise differences was then applied to estimate p-value and to detect significant differences between models.

III. RESULTS

Figure 1 illustrates the placement of accelerometric, gyrometric, and LiDAR sensors. For the analysis of the symmetry coefficient, signals from sensors positioned on the left and right arms and legs were utilized. The subsequent evaluations were performed using the MATLAB 2025a (MathWorks, Massachusetts, USA) computational environment. Training of the two-layer NN required less than 10 minutes on a standard workstation (Intel i7 CPU, 16 GB RAM).

Each set of records that included data acquired with the selected sampling frequency of 200 Hz by all sensors for each individual formed a multichannel signal about 65 seconds long. Two time windows used for accelerometric and gyrometric data analysis in both the frequency and scale domains were approximately 15 seconds long.

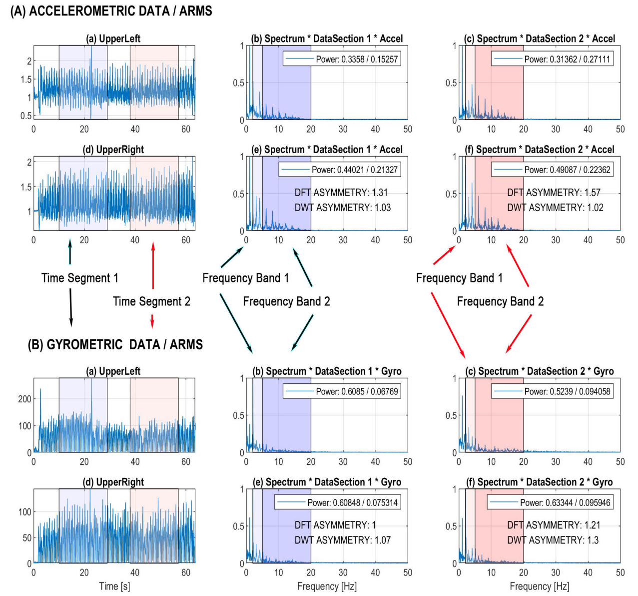

FIGURE 2. Data processing of a selected individual with the normal gait presenting (A) accelerometric data and (B) gyrometric data recorded in two time segments of the (a) upper left and (d) upper right part of the body with associated spectral components in (b,e) the first and in (c,f) the second time region with highlighted frequency bands used for data analysis.

Figure 2 presents data acquired and processed during separate steps of a selected individual with the normal gait based on accelerometric and gyrometric data recorded in two time segments on the upper left and upper right arm. Associated spectral components in two frequency bands are then used for data analysis using data in the first and the second time regions. Figures 2(b,c,e,f) present highlighted frequency bands used for signal features extraction. This process was applied for all individuals in the set of individuals with the normal and abnormal gait.

The choice of frequency ranges was based on literature [46] and confirmed by pilot spectral analysis of our dataset, showing dominant leg oscillations between $1 - 2.5$ Hz and arm swing at $2 - 5$ Hz. The second frequency range used for normalization included components in the band $\langle 2.5, 20\rangle$ Hz for the legs, and $\langle 5, 20\rangle$ Hz for the arms. The relative power within these ranges was calculated by the DFT using Eq. (5). Similarly, the DWT was applied using the Daubechies wavelet function of the second order at the third decomposition level.

Numerical results for separation of normal and abnormal gait features by the 5-nearest neighbour (5-NN), Bayes, support vector machine (SVM), and the two-layer neural network (NN) methods are presented in Table 2. The accuracy of each model is evaluated as the mean of accuracies of 10 data folds presenting associated 95% confidence intervals.

TABLE 2. Results of classification of walking motion by the 5-nearest neighbour (5-NN), Bayes, support vector machine (SVM), and the two-layer neural network (NN) methods using accelerometric (A) and gyrometric (G) data. Features are evaluated by the discrete Fourier (F) and discrete wavelet (W) transform as (i) the energy ratio in two frequency bands (or scales), and (ii) the mean energy in the selected frequency band (or scale). Separate columns present mean accuracy (ACC) [%], 95% confidence intervals [%], and mean 10-fold cross validation (CV) errors for each classification method with the highest characteristics in each sensor position category emphasized.

Set	*5-NN*			*Bayes*			*SVM*			*NN*		
	ACC	*Confidence*	*CV*	*ACC*	*Confidence*	*CV*	*ACC*	*Confidence*	*CV*	*ACC*	*Confidence*	*CV*
(i) ENERGY MULTI-BAND RATIO FEATURES												
1-Legs-AF	81.2	63.2-96.2	0.113	78.2	61.2-95.1	0.145	82.7	64.9-99.5	0.097	**84.7**	**66.1-100.0**	**0.075**
2-Legs-GF	65.1	48.8-81.3	0.285	70.1	52.3-87.9	0.231	65.1	48.7-81.4	0.285	75.2	57.5-92.6	0.177
3-Legs-AW	63.5	46.2-80.9	0.301	55.5	39.4-71.5	0.387	52.9	35.5-70.4	0.414	76.7	58.2-95.1	0.161
4-Legs-GW	59.5	43.6-75.4	0.344	62.6	43.5-81.6	0.312	60.5	46.2-74.8	0.333	73.1	55.5-90.7	0.199
MEAN	67.3		0.261	66.6		0.269	65.3		0.282	77.2		0.156
5-Arms-AF	68.6	51.7-85.4	0.247	67.1	51.6-85.5	0.253	67.6	50.0-85.2	0.258	79.2	60.9-97.3	0.134
6-Arms-GF	65.6	49.2-81.9	0.280	72.1	54.6-89.7	0.210	68.1	50.9-85.2	0.253	83.2	64.4-100.0	0.091
7-Arms-AW	63.5	47.2-79.9	0.301	74.1	57.2-91.1	0.188	69.1	51.4-86.8	0.242	76.7	57.3-95.4	0.161
8-Arms-GW	60.0	42.4-77.6	0.339	62.5	47.8-77.3	0.312	58.5	41.2-75.8	0.355	**86.3**	**68.4-100.0**	**0.059**
MEAN	64.4		0.292	69.0		0.241	65.8		0.277	81.4		0.111
(ii) SINGLE-BAND ENERGY FEATURES												
1-Legs-AF	70.6	52.8-88.4	0.226	67.6	51.6-83.6	0.258	62.5	47.0-78.0	0.3120	79.2	62.1-96.3	0.134
2-Legs-GF	79.7	62.0-96.6	0.129	80.7	62.9-97.7	0.118	82.7	65.4-99.5	0.097	**83.7**	**64.2-100.0**	**0.086**
3-Legs-AW	57.0	40.4-73.5	0.371	43.3	30.7-56.0	0.516	57.5	39.0-76.0	0.366	76.7	58.1-95.1	0.161
4-Legs-GW	66.1	48.9-83.2	0.274	70.1	52.5-87.7	0.231	68.6	51.3-85.9	0.247	82.2	64.3-99.3	0.102
MEAN	68.4		0.250	65.4		0.281	67.8		0.256	80.5		0.121
5-Arms-AF	78.2	60.3-94.0	0.145	69.6	53.1-86.1	0.237	69.1	53.2-85.0	0.242	**87.8**	**69.1-100.0**	**0.043**
6-Arms-GF	60.0	44.3-75.7	0.389	71.6	54.7-88.5	0.215	65.6	47.3-83.8	0.280	83.2	65.4-98.9	0.091
7-Arms-AW	70.1	53.3-86.9	0.231	68.1	51.7-84.5	0.253	65.6	47.7-83.4	0.280	77.2	58.7-95.6	0.156
8-Arms-GW	64.0	45.6-82.5	0.296	64.5	48.7-80.4	0.290	61.5	43.8-79.2	0.323	80.2	61.3-98.7	0.124
MEAN	68.1		0.265	68.5		0.249	65.5		0.281	82.1		0.104
TOTAL MEAN	67.1		0.267	67.4		0.260	66.1		0.274	**81.1**		**0.123**

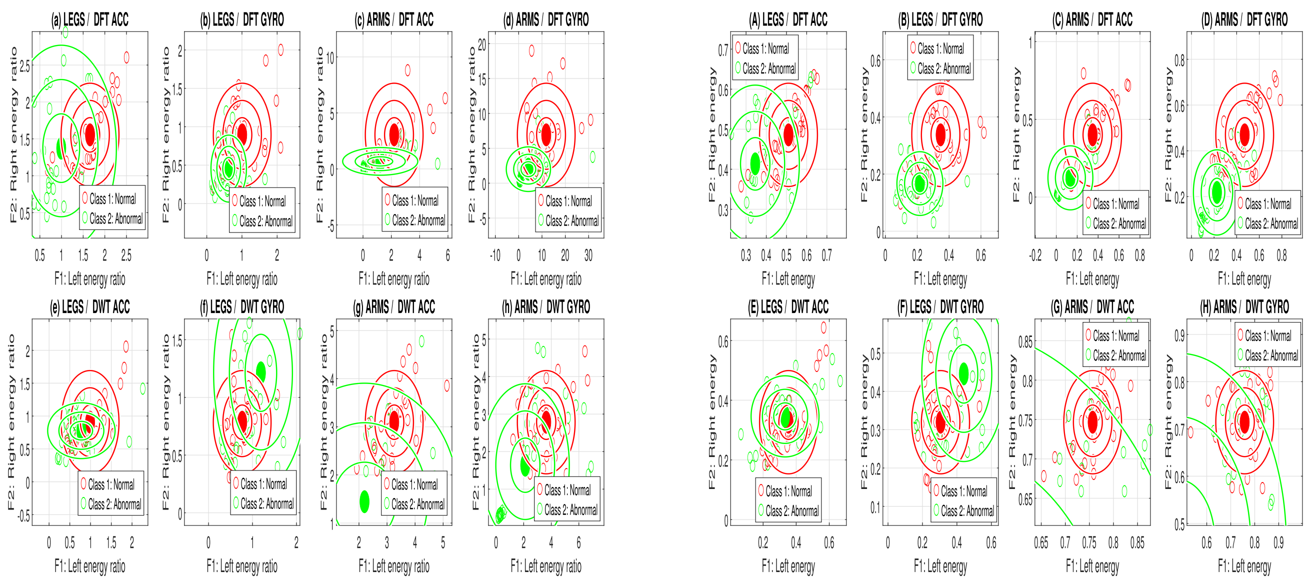

FIGURE 3. Motion classification comparing the control set (Class 1 - red) of 14 individuals) and individuals with gait disorders (Class 2 - green) of 17 individuals using DFT and DWT features of accelerometric and gyrometric data recorded on legs and arms using (a-h) the multi-band ratio of energy in two different frequency regions and (A-H) the single-band relative energy in selected frequency region, with mean values of individual clusters and *c* multiples of standard deviations for *c* = 0.5, 1, 1.5 associated with individual clusters.

These values were then used to perform paired t-tests between models.

Table 2(i) is based on the two-band energy ratio of data recorded on the left and right leg and arm using accelerometric (A) and gyrometric (G) data by discrete Fourier (F) and discrete wavelet (W) methods presenting associated accuracy (ACC) and the mean of 10-fold cross validation (CV) errors repeated three times to reduce problems of overestimation. Similar results based on relative energy features presented in Table 2(ii) use single band analysis. Results of multiband analysis based on more features enabled better separation of individual classes. The paired t-tests between models pointed that NN performance was significantly higher ($p < 0.05$) than others.

The distribution of walking features highlights the degree of asymmetry in motion patterns. Results obtained from both

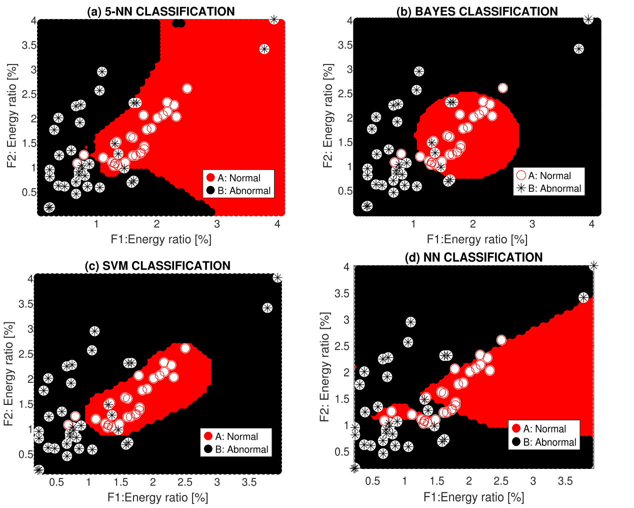

FIGURE 4. Classification of walking motion by energy ratio of accelerometric data recorded on the left and right leg by (a) the 5-nearest neighbour (5-NN), (b) Bayes, (c) support vector machine (SVM), and (d) the two-layer neural network (NN) methods.

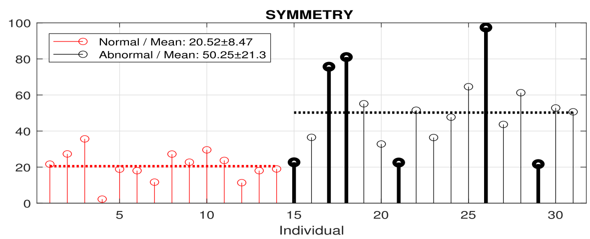

FIGURE 5. Symmetry coefficient of normal and abnormal gait using the relative mean frequency components using the ratio of relative energy in frequency bands F1∈ ⟨1, 2.5⟩ Hz and F2∈ ⟨2.5, 20⟩ Hz, evaluated for accelerometric sensors on the left and right legs with emphasized individuals having the symmetry criterion below or above standard deviations limits related to the mean of this criterion for the abnormal gait.

the DFT and DWT analyses are comparable; however, the DFT approach yields lower standard deviations, indicating a more consistent evaluation of symmetry.

Figure 3 presents distribution of motion patterns comparing the control set (Class 1: red) of 14 individuals and 17 patients with gait disorders (Class 2: green) using DFT and DWT features of accelerometric and gyrometric data recorded on legs and arms using (a-h) the multi-band ratio of energy in two frequency regions and (A-H) the single-band energy in the selected frequency region, with mean values of individual clusters and c multiples of standard deviations for $c = 0.5, 1, 1.5$ associated with individual clusters.

Motion classification using the multi-band ratio of DFT features for accelerometric data recorded on the left and right legs is presented in Figure 4. Associated numerical results evaluated by selected classification methods are summarized in the first part of Table 2(i).

Figure 5 presents the symmetry coefficients of 14 individuals with normal gait and 17 individuals with abnormal gait using the ratio of relative energy in frequency bands F1∈ ⟨1, 2.5⟩ and F2∈ ⟨2.5, 20⟩ Hz. Symmetry coefficients of PD individuals with this coefficient above or below the mean±its standard deviation are in bold. Patients 17, 18, and 26 exhibited the lowest (i.e., most pathological) symmetry coefficients, consistent with severe post-stroke hemiparesis. By contrast, patients 15, 20, and 26 showed only modest elevations above the group mean, indicating mild hemiparesis following their cerebrovascular event.

TABLE 3. Mean symmetry coefficients and their standard deviations (Std) evaluated by energy ratio of data recorded on the left and right legs (L) using accelerometric (A) and gyrometric (G) data based on relative energy features using DFT (F) and DWT (W) with the highest value in bold.

MOTION SYMMETRY BASED ON ENERGY RATIO FEATURES

Set	*Normal Gait*		*Abnormal Gait*		*Ratio*
	Mean	*Std*	*Mean*	*Std*	
1-Legs-AF	16.5	8.2	54.3	34.2	**3.3**
2-Legs-GF	44.8	17.6	59.0	41.0	1.3
3-Legs-AW	24.5	12.0	46.2	18.6	1.9
4-Legs-GW	38.8	24.1	43.0	24.3	1.1
MEAN					1.9

Table 3 presents mean symmetry coefficients and their standard deviations (STD) evaluated by the energy ratio of data recorded on the left and right legs using accelerometric (A) and gyrometric (G) data based on relative energy features using DFT and DWT. The highest ratio of 3.3 of these values for abnormal and normal gait was achieved by analysis of accelerometric signals recorded on legs. The mean ratio of symmetry coefficients separating abnormal gait was 1.9 for a set of individuals under study.

IV. DISCUSION

Advanced DSP techniques have been employed to analyze gait abnormalities between PD patients and healthy controls. Motion symmetry refers to the balance and consistency between movements of the left and right sides of the body during activities such as walking, running, or rehabilitation exercises. Symmetry can be assessed using spatiotemporal parameters (e.g., stride time, step length) or features derived from gait signals, such as frequency components extracted from accelerometric data. While multiple sensors enhance robustness, in some specific applications, a single sensor [23], [29] positioned at the optimal location (at the lower back, L5) can be used.

This study focuses on using accelerometers and gyrometers for estimation of gait features through the DFT and DWT methods in selected frequency bands for two sets of individuals. This dual approach can improve separation between normal/abnormal gait, reducing variance of symmetry coefficients compared to single-domain analysis. Neural network classifiers achieved the highest performance, with a mean accuracy of 81.1% and a cross-validation error of 0.123, using data from sensors placed on the left and right sides of the body. The highest accuracy of 87.8% was achieved for classification of arm features.

The proposed symmetry coefficient quantifies the level of asymmetry, with a value of 0 indicating perfectly symmetric motion. In this case, the average symmetry coefficient was calculated to be 21% (standard deviation 8.5) for controls and 50% (standard deviation 21.3) for patients with the abnormal gait using the ratio of relative power.

The asymmetrical motion detected by mathematical analysis of accelerometric data is in agreement with diagnosis estimated by experienced neurologists for 15 out of 17 individuals (88%) and its comparison with abnormal gait analysis using the energy ratio of accelerometric data. Neurologist's assessments was based on the NIHSS scale and clinical gait evaluation (stride length, arm swing). The ratio of mean values of coefficients of symmetry for individuals with the normal and abnormal gait is 1.9 for the given set of patients. Asymmetry in accelerometric and gyrometric motion data can be used as a feature for PD detecting or monitoring. In fact, motor asymmetry is one of the hallmark signs of early PD and has been widely studied using wearable sensors.

The symmetry coefficient mirrors the severity of gait impairment. Unlike some prior works that use only one modality or a limited feature set, we demonstrate that combining DFT/DWT features improves classification robustness. Furthermore, we validate results against clinical scores (NIHSS), providing translational clinical relevance. The proposed methodology forms an alternative to further methods of motion disorders analysis using depth camera sensors, sensors of mobile phones, exercise bicycles, or single accelerometric sensors placed on the body in the optimal position with wireless data transmission.

Limitations of the present study are in the small size of the set of patients and the mixture of individuals with Parkinson's disease with stroke patients. Additional problems are listed in the latest references [47]. Future studies should be based on more extensive datasets and the separation of patients with different diseases. The present methodology and results motivate future research based on the deep learning strategy to evaluate probabilities of specific gait disorders. More extensive datasets will be included in future studies to reduce present limitations of independent testing.

Motion analysis is closely related to the development of AI-powered wearables for continuous symmetry monitoring and advancements in high-quality accelerometer technology. Key research areas include optimizing sensor placement for reliable data acquisition and developing robust AI models that generalize effectively across diverse populations.

V. CONCLUSION

Clinical gait analysis plays a critical role in the diagnosis and management of locomotor impairments. Such analysis is vital for assessing disease severity, enabling early detection, and monitoring progression.

The present study shows how functional transforms, including the DFT and DWT, are powerful tools for analyzing gait symmetry providing time-frequency and time-scale representations of data. These methods enable the detection and evaluation of subtle temporal and frequency features in gait patterns. The DFT offers a constant resolution in both time and frequency domains, while the DWT allows for multi-resolution analysis, making it particularly effective for identifying walking patterns distributed across a broad range of frequencies.

The paper presents a complex multisensor approach to motion data analysis that provides detail facts related to gait habits during the treatment and rehabilitation. Its limitations for diagnostic purposes of neurological patients with the most severe motion disorders are in the fact that some of them use supporting devices that can affect data analysis.

Future studies should compare the accuracy of upper-limb versus lower-limb symmetry metrics in individuals with mild post-stroke hemiparesis and in neurologically healthy controls. Motion asymmetry estimation can be further enhanced through artificial intelligence. AI techniques can train classifiers to distinguish between symmetric and asymmetric patterns using wavelet-derived features to detect both coarse and fine asymmetries. Sampling frequency of 200 Hz will enable future extension of studies to tremor and fine-motor signal analysis. The combination of AI and accelerometers provides a robust framework for symmetry analysis. Accelerometers capture raw motion data, while AI processes and interprets this data to quantify and evaluate symmetry metrics. Convolutional neural networks and recurrent neural networks can be employed to extract spatial and temporal features, respectively, analyzing sequential data to capture motion dynamics over time.

Applications of gait symmetry analysis include detecting asymmetries in patients with conditions such as Parkinson's disease, stroke, or cerebral palsy. Other important use cases involve tracking recovery progress after injuries or surgeries, monitoring rehabilitation exercises, and optimizing performance in various sports activities.

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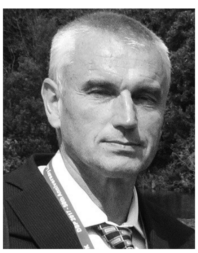

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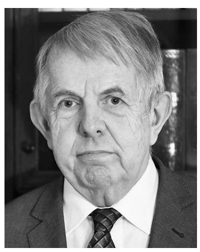

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