REVIEW

Gait Analysis in Neurologic Disorders

Methodology, Applications, and Clinical Considerations

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Abstract

Gait and balance disorders are a leading cause of morbidity, mortality, and disability in central and peripheral neurologic disorders. Neurologic gait disorders are classically evaluated with a clinical examination and visual pattern recognition. Gait patterns such as a parkinsonian or ataxic gait may have distinct etiologies and are assessed using the neurologic physical examination and validated clinical scales. Technological advances have made gait analysis more accessible, allowing precise objective measurement of gait and balance deficits. Gait analysis may be more sensitive at detecting change compared with a physical examination alone. It has the potential to augment clinical diagnosis, track disease progression, and evaluate response to therapies in clinical trials. Additional applications of gait analysis include early disease screening, discriminating between conditions that have similar gait profiles, and use of quantified gait parameters to predict future outcomes. Numerous devices are now available to conduct gait performance measurements in the laboratory, clinic, or real-world settings. With the rapid growth of gait analysis technology and application of artificial intelligence to these data, there are clinical and research implications that should be carefully considered when evaluating patients with neurologic disorders. Important factors include the clinical or research question, reliability and validity of the method used, and the effect of environmental and patient factors. Knowledge of gait analysis technology is essential for clinicians to implement this tool in clinical practice or research and critically analyze literature on the topic in neurologic diseases. In this narrative review, we provide an overview of normal gait function, an appraisal of available gait analysis technologies (merits and applications), implications for clinicians and researchers, recent advances in gait analysis for neurologic disorders, and future considerations.

Introduction

Why should we talk about gait analysis in neurologic disorders? With a growing aging population, the global burden of stroke, dementia, and Parkinson disease (PD) is projected to increase.[1,2] These and other neurologic conditions cause gait and balance abnormalities, which are a leading cause of disability and death, and remain one of the most challenging aspects to treat. Gait impairment also leads to falls, loss of functional independence, and need for out-of-home placement. There are gaps in our understanding of gait abnormalities in neurologic diseases: (1) neural mechanisms of gait and balance dysfunction in some conditions remain incompletely understood; (2) there is a lack of precise quantification and available clinical scales are not sensitive to small or early changes; (3) there is a lack of adequate treatments. In most neurologic diseases where symptomatic or even disease-modifying therapies are available, cumulative disability from gait impairment often persists and is suboptimally treated. For example, levodopa may alleviate most motor symptoms in PD, but gait and balance impairment may not respond, especially as the disease progresses.

Gait analysis has the potential to be a valuable tool to advance scientific progress in these areas by providing objective quantification of gait disorders. Advances in medical devices, software, computing power, and the application of artificial intelligence and machine learning (AI/ML) have led to a rapid growth of gait analysis technology.[3] These advances can facilitate early and

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Glossary

3D = 3-dimensional; **AI** = artificial intelligence; **COM** = center of mass; **COP** = center of pressure; **DMO** = digital mobility outcome; **GRF** = ground reaction force; **IMU** = inertial measurement unit; **ML** = machine learning; **mocap** = motion capture; **MS** = multiple sclerosis; **PD** = Parkinson disease; **ROM** = range of motion; **ST** = spatial-temporal.

precise quantification of deficits, detection of preclinical states, measurement of patient-centric real-world outcomes,[4] assessment of response to therapies, and investigation of disease mechanisms in association with other disease-specific biomarkers and neuroimaging.[5] However, important limitations remain in the current state of research using gait analysis, especially in neurologic disorders. Experimental methodology is highly variable (experimental designs and devices used); there is often a lack of device validation in disease groups, especially for wearable technologies; and few longitudinal studies exist. Gait analysis technology encompasses a broad range of methods and devices that produce distinct data with unique considerations that may affect generalizability and reproducibility of the findings.

Gait analysis has increasing applications in clinical care and translational research. It is valuable for a neurologist to be familiar with gait analysis technologies. The goal of this narrative review was to provide practicing neurologists with foundational knowledge of gait analysis terminology (data and devices), its applications, limitations, recent advances, and future implications for clinical practice and research.

Methods

This article is a structured narrative review aimed at providing a broad overview of gait analysis technology, recent impactful clinical and translational research in this area, and implications for the future. We focused on articles published in the past 3 years (2022–2024 inclusive) and conducted PubMed search using keywords including but not limited to "gait," "gait analysis," "digital gait analysis," and "digital health technology," along with the context of "neurological disease," "neurological gait," "Parkinson's disease," "stroke," "ataxia," "multiple sclerosis," "neuropathy," and "neuromuscular disease." Because this is not a systematic review or meta-analysis, we did not systematically compile evidence, nor do we provide specific evidence-based recommendations. Currently, there is a lack of consistent data that would be required to provide strong evidence-based recommendations; hence, we discuss recent advances and identify future considerations to facilitate research and consensus in the field.

Standard Protocol Approvals, Registrations, and Patient Consents

Because this is a narrative review and no patient data were used, this article was exempt from institutional review board review and no consent procedures were required.

Components of Gait

Gait Cycle

Human locomotion comprises a series of periodic movements that lead to forward propulsion of the body. This is achieved through a complex interaction between the musculoskeletal, neuromuscular, and sensory systems. A "gait cycle" is composed of 2 steps and starts from initial contact of the heel of 1 foot (heel strike) and ends with subsequent heel strike of the same foot (Figure 1).[6] Neurologists visually observe this sequential movement during the gait examination to detect features such as dampening of the heel strike, short step, or limited elevation of the swinging leg (shuffling), for example, in parkinsonian gait. The gait cycle comprises stance (60%) and swing (40%) phases that can be calculated for each leg. Single-limb swing time is reduced in bradykinetic conditions while stance may be reduced for a painful or unstable limb.

Gait and balance parameters are described in detail and summarized in Table 1.

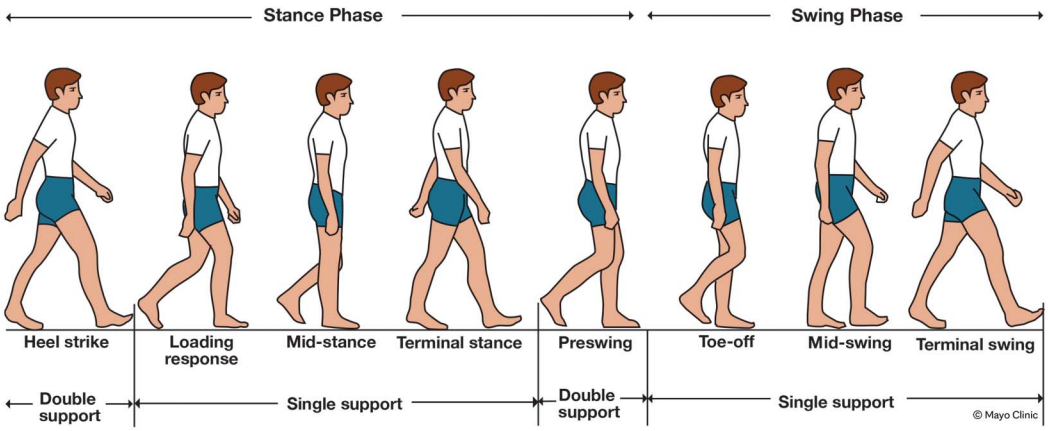
Spatial-Temporal Parameters

Spatial-temporal (ST) parameters, also called temporal distance parameters, assess distance covered over time and include velocity, stride or step features (length, width, and variability given in Figure 2), and duration of gait cycle phases (support, swing, or stance times). These metrics provide a global assessment of gait function. A slow pace (slower than normal velocity, short stride/step length) can be seen in a variety of neurologic and orthopaedic disorders that impair mobility. Variability (measured by standard deviation or coefficient of variation) is increased in disorders of coordination such as ataxia, hyperkinetic gait, and postural instability. Time spent in each phase of the gait cycle (swing vs stance) can be used to assess rhythm and estimate stability. Individuals with a slow pace and imbalance tend to spend more time in double support (both feet on the ground). ST parameters can be useful to assess asymmetry between the right and left legs. For example, a painful, weak, bradykinetic, or unstable leg may demonstrate a shorter step length or single support time.

Kinematics

Kinematics quantify segmental motion in degrees at each joint in the frontal, sagittal, and transverse plane. Three-dimensional (3D) video motion capture (mocap) is usually required for kinematic analysis, but measurements can also be obtained from a series of inertial measurement units (IMUs) or pose estimation algorithms applied to videos to calculate motion across body segments. Movements in the frontal plane are abduction and adduction, movements in the sagittal

Figure 1 Phases of the Gait Cycle



The gait cycle of the right leg (closest to the viewer) is shown. The gait cycle starts with initial heel strike after which weight is transferred onto this foot throughout the stance phase, moving from the heel to the midfoot and then the anterior foot in terminal stance. The stance phase ends with the preswing and then toe-off, marking the beginning of the swing phase. The gait cycle ends with the subsequent heel strike of the right foot at the end of terminal swing. Used with permission of Mayo Foundation for Medical Education and Research. All rights reserved.

plane are flexion/extension (anterior/posterior pelvic tilt), and movements in the transverse plane are internal or external rotation. Active and passive range of motion (ROM) at a joint is the maximal range of excursion available and should be assessed on examination. The segmental motion seen on kinematics in neurologic disorders is influenced by both the available joint ROM (limited by osteoarthritis, contracture, etc.) and neurologic mobility impairment from neuromuscular weakness, bradykinesia, or spasticity. Restricted mobility can cause abnormal transmission of weight between body segments leading to instability.

Kinetics

Kinetics is the assessment of forces that cause motion. This includes ground reaction force (GRF), moment of force, and power (rate of change of force); the latter 2 are calculated at individual joints. GRFs act in the vertical, mediolateral, and anteroposterior direction as the body progresses through the stance phase. Selective neuromuscular control modulates forces at each joint and leads to a specific pattern of limb movement and stability. Abnormal CNS motor regulation (e.g., PD or cognitive impairment), neuromuscular weakness (e.g., foot drop or myopathies), or musculoskeletal issues (e.g., osteoarthritis) may alter the magnitude and directional control of forces required for stable forward locomotion. Kinetics can be accurately quantified using mocap systems and force plates or estimated using IMUs.

Surface Electromyography

Surface or fine-wire intramuscular electrodes are used to gather the EMG signal. EMG data can be coupled with kinematic and kinetic data to evaluate relative contribution from different muscles to explain the pattern of movement observed. Pathologic muscle activity can be seen in dystonia (high-amplitude, phasic, or tonic co-contraction of agonist and antagonist muscles; activation of surrounding muscles; and shift in the median power frequency of dystonic muscles).

Balance Assessment

Static stability (balance while standing) is measured using sway that evaluates sensory-motor integration.[7] Sway is measured with the trajectory of the center of mass (COM) using a mocap system or IMU, or the trajectory of center of pressure (COP) using a force plate. Dynamic stability (balance while walking or doing other activities) is the ability to maintain the COM over the base of support without losing postural control and can be assessed using the limit of stability or dynamic stability margin.[8] These concepts are presented in Figure 3 and Table 1. In a laboratory setting, dynamic stability margin is calculated using synchronized data from mocap and force plates. In the real-world setting, the acceleration of the COM can be estimated using data from a truncal IMU. Abnormal stability measures have been associated with fall risk in the elderly and in neurologic disorders that impair sensory-motor integration such as stroke, PD, ataxia, or multiple sclerosis (MS).

Critical Appraisal of Gait Analysis Methods

Various methods for objective gait and balance assessment, each with its own benefits and limitations, are available (Figure 4 and Table 2). These factors should be considered when evaluating scientific literature or selecting the best option for clinical or research use.

Motion Capture Systems

Highly detailed and accurate assessments can be performed using marker-based mocap in a laboratory. A large space with infrared cameras placed in a 3D fashion around the recording volume is needed. The participant is dressed in minimal clothing, and retroreflective markers are placed on designated anatomical sites. Infrared light reflected by these markers is

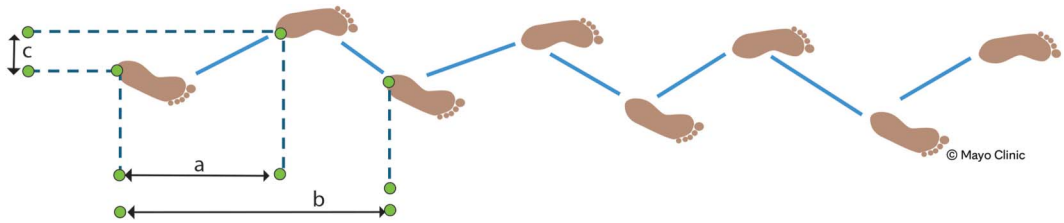
Table 1 Gait Analysis Parameters

Variable	Measurement (units)
Spatial-temporal	
Velocity	Distance covered per unit of time (cm/s or m/s)
Stride length	Distance between 2 subsequent ipsilateral heel strikes (m or cm)
Step length	Distance between 2 subsequent contralateral heel strikes (m or cm)
Stride/step width	Distance between the midpoint of the 2 heels (m or cm)
Variability	Standard deviation or coefficient of variance of any spatial-temporal parameter
Cadence	Steps per unit time (steps per minute)
Single support time (R/L/total)	Time spent on 1 foot during the gait cycle (minute, second, or % of gait cycle)
Double support time	Time spent on both feet during the gait cycle (minute, second, or % of gait cycle)
Swing time (R/L/total)	Time spent during the swing phase (minute, second, or % of gait cycle)
Stance time (R/L/total)	Time spent during the stance phase (minute, second, or % of gait cycle)
Static balance (AP/ML)	
Sway path length	Total distance traveled by the COP during standing (m or cm)
Sway velocity	Speed of the COM or COP trajectory (m/s)
Sway acceleration	Rate of change of COM or COP velocity (m/s^2 or cm/s^2)
Sway area	Total area covered by the COP trajectory (m^2 or cm^2)
Sway amplitude	Maximum distance between 2 points on a stabilogram (m or cm)
RMS sway	Accounts for frequency and amplitude of sway (m/s^2)
Jerk	Rate of change of acceleration (m^2/s^5)
Dynamic balance	
Dynamic stability margin	Distance between the xCOM and the boundaries of BOS (m or cm). xCOM is the predicted forward location of the COM based on the acceleration
Limit of stability	The maximum displacement of the COP beyond the BOS (leaning) that an individual can tolerate without losing balance (degrees)
Kinematic	
Joint angle	Relative angle between 2 adjacent bone segments at the joint of articulation measured during phases of the gait cycle (degrees)
Joint motion	Excursion at the joint during the gait cycle; a combination of active and passive range of movement available during the gait cycle (degrees)
Kinetic	
Moment	Turning effect of a force on a joint; product of force and perpendicular distance of the force vector from the axis of movement (Nm)
Force	Ground reaction forces and muscular forces acting on a joint (N)
Power	Product of joint moment and angular velocity (watts)

Abbreviations: AP = anteroposterior; BOS = base of support; COP = center of pressure; COM = center of mass; ML = mediolateral; L = left; N = newton; Nm = newton meter; R = right; RMS = root mean square (square root of the mean of squared sway values); xCOM = extrapolated center of mass.
Descriptions of most relevant and commonly used gait and balance parameters.

captured using video cameras to track movement. Stereophotogrammetric software converts the time-series data of marker location obtained from each camera into marker trajectories in 3D space. The marker trajectories are used to form an orthogonal coordinate system for each body segment, and movement is calculated using the rotation matrix between 2 segments. Although marker-based mocap is accurate and reliable, it requires a large space, technical expertise, longer examination time (2–3 hours), and costly equipment. Marker-based mocap has been used to study neurologic conditions

Figure 2 Visualization of Spatial-Temporal Parameters



Commonly measured spatial-temporal parameters are shown. Distance covered over measured time is used to deduce velocity. a: step length, b: stride length of the right foot, c: step width. Used with permission of Mayo Foundation for Medical Education and Research. All rights reserved.

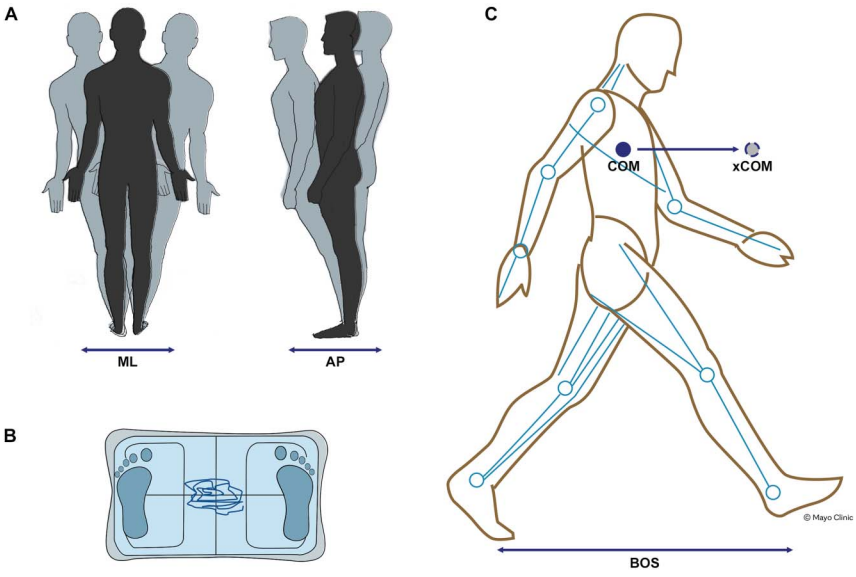
and remains the gold standard for validation of other technologies.[9]

Marker-less mocap uses a depth or red-green-blue video. Pose estimation software is used to estimate joint centers to extrapolate movement of body segments and calculate gait and balance metrics. Joint center localization is not always consistent when compared with marker-based mocap. However, deep learning–based augmentation strategies developed in recent years have reduced errors in anatomical localization.[10] Marker-less mocap is more accessible and can be implemented faster in a variety of settings (laboratory, clinic, or real-world settings).[11] Specialized software is required for pose estimation and subsequent data analysis. Quality of data may be affected by video quality, recording volume, lighting, and clothing if obstructive. Marker-less mocap is comparable to marker-based methods regarding accuracy and reliability of ST metrics but may be less accurate for frontal and transverse plane ROM.[9] In neurologic disorders, marker-less mocap has been used successfully to detect global gait patterns as a result of therapy on and off state in PD.[12]

Wearable Devices

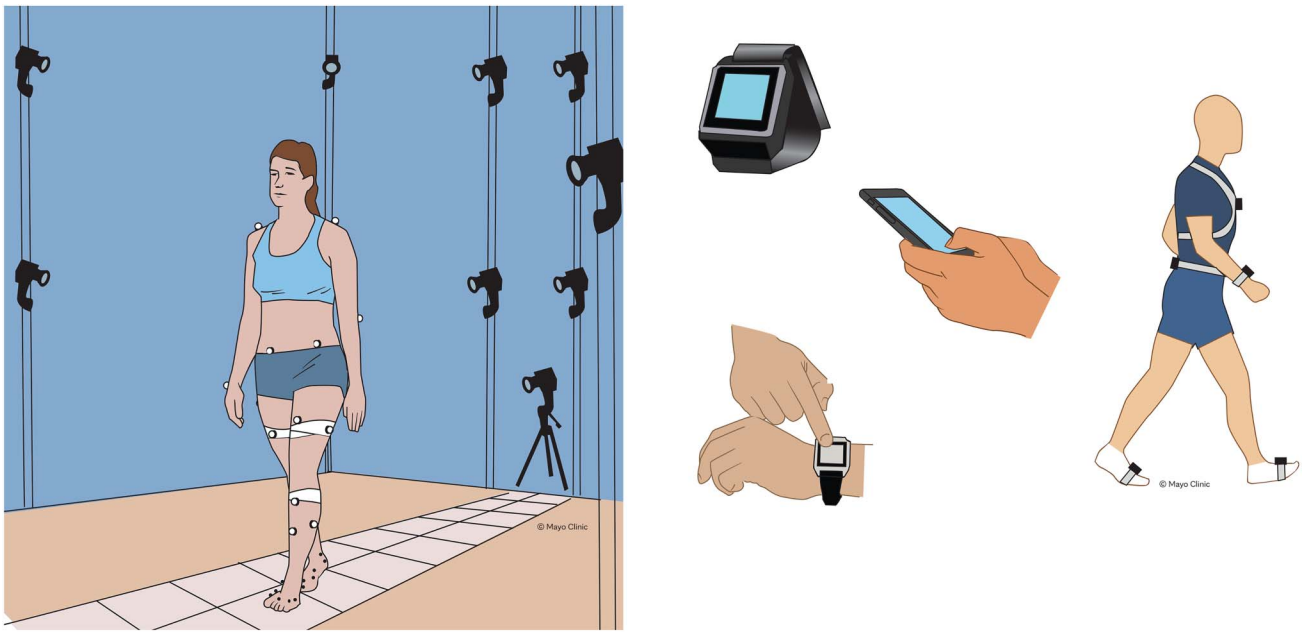
Wearable devices are increasingly being used for gait analysis in neurologic diseases.[13] Their portable nature allows for use in a laboratory and clinic or for remote monitoring in a free-living environment. Wrist-worn accelerometers can quantify active and rest periods to assess global activity levels, energy expenditure, and steps. Detailed gait and balance parameters can be obtained from IMUs, which are a combination of accelerometer, magnetometer, and gyroscope and measure angular acceleration and directional movement. IMUs or accelerometers can be used as a single sensor on the wrist, ankle, or trunk, or as a set of multiple sensors on the limbs and trunk for more detailed gait and balance assessment. Number and location of sensors, analytical algorithms used, and experimental conditions in existing literature are highly variable, which can limit comparison across studies. IMUs have been shown to detect clinical deficits in several neurologic conditions such as stroke, spinocerebellar ataxia, MS, PD, and progressive supranuclear palsy; however, longitudinal studies and rigorous validation are required to determine clinical

Figure 3 Conceptual Overview of Balance Measurement



Panel A shows measurement of static stability using sway in the anteroposterior (AP) and mediolateral (ML) direction. This can be measured using body-worn sensors or force plates. Panel B shows a force plate that can assess sway by measuring the trajectory of the center of pressure (COP) shown as the squiggly line. Panel C shows the concept of dynamic stability. The speed of movement determines where the center of mass (COM) is expected to be during forward locomotion, referred to as extrapolated COM (xCOM). To maintain stability, the base of support (BOS) should be able to catch up with this xCOM during walking. Used with permission of Mayo Foundation for Medical Education and Research. All rights reserved.

Figure 4 Overview of Gait Analysis Methods



Left panel: Marker-based motion capture. Retroreflective markers shown as small dots are affixed to specific anatomical sites. Cameras record the three-dimensional trajectory of markers. Right panel: Other methods of gait analysis are shown including smart devices (phones and watches), body-worn devices including inertial measurement units that can be affixed to a single location such as the wrist, or multiple locations (feet, wrist, lower back, and chest), as shown for more detailed assessment of full-body movement. Used with permission of Mayo Foundation for Medical Education and Research. All rights reserved.

utility.[13] For all wearable devices, validation compared with gold standard methods should be performed with any new device or new target disease group to ensure accuracy and reliability. Best practices and consistent methodologies are needed for reproducibility and comparability across studies.

Force Plates

Force plates quantify the direction and magnitude of GRFs, which can be used to calculate a variety of static and dynamic balance parameters. In laboratory-based settings, force plates can be time synchronized with mocap. Static balance (standing) and dynamic balance (walking) can be measured accurately, but differences between force plates may be as high as over 80-mm^2 change in COP sway area; if this error is clinically significant in a population, using the same force plate for longitudinal assessment is recommended.[14] Force plate measurements can effectively measure pathologic instability and its severity in neurologic diseases such as PD, MS, ataxia, and stroke.[15-17]

Pressure Sensors

Foot/floor contact is measured with an instrumented pressure-sensitive walkway to calculate gait metrics. Patients are asked to walk on this walkway as they normally would in day-to-day life with or without a gait aid. Each step activates pressure sensors. While the magnitude of force is not measured, the relative location and motion of each step are used to calculate ST parameters. Balance measurements can be derived using relative motion of the COP. The movement of the COM is not directly measured and is implied from COP data. A systematic review and meta-analysis conducted by the Office of Product Evaluation and Quality, of the US Food and Drug Administration, concluded that the pressure-sensitive walkway is accurate and reliable for measurement of 25 ST gait parameters evaluated.[18] For example, velocity had an estimated bias of 0.006 m/s with limits of agreement between −0.07 and 0.083 m/s.

Pressure-sensitive shoe insoles have been developed as a wearable alternative for acquiring ST parameters, GRFs, and their trajectory. These insoles are less accurate and, according to some reports, may underestimate vertical GRFs by as much as 200–600 N, and underestimate COP trajectory lengths by up to 10 cm.[19]

Other Methods

Smartwatches and smartphones containing accelerometers can calculate basic ST parameters and have been evaluated in MS, ataxia, and PD.[20,21] These devices are easily accessible and nonintrusive and enable scalable real-world remote assessments. Measurements may be affected by anthropometric factors, patterns of use, and phone/watch placement. Secure transfer of data is an important consideration. Validity and reliability studies are needed for most of such devices and their application.

Gait Analysis in Neurologic Gait Disorders

What are some findings that can be expected on gait analysis in neurologic gait disorders? Common neurologic gait

Table 2 Overview of Gait Analysis Devices

Device	Method	Strengths	Limitations
Marker-based mocap	3D location and motion of retroreflective markers placed on the body is tracked by cameras	Accurate Reliable Detailed evaluation	Laboratory environment only Extensive time, space, and expertise required Soft-tissue and marker movement can affect accuracy
Marker-less mocap	Pose estimation software uses red-green-blue or depth video to track movement of body segments	Accessible Cost effective Several video sources can be used Real-world assessment	Accuracy dependent on recording volume, video quality, clothing, and number of cameras
Pressure walkway	A mat or walkway equipped with pressure sensors is activated by each foot fall. Used to calculate spatial-temporal parameters	Accurate Spatial-temporal and some balance measures can be obtained	Can be expensive Dedicated space required, not easy to move around No real-world evaluation Does not quantify forces
Force plates	Quantify magnitude and direction of GRF to assess stability parameters	Accurate assessment of balance Both portable and floor embedded options available	Differences exist between different plates Multiple plates or alternative methods are needed for spatial temporal parameters
Wearable sensors (accelerometers, IMU)	Linear and angular acceleration of the body segment the sensor is attached to is measured IMUs contain an accelerometer, magnetometer, and a gyroscope	Inexpensive Easy to use Portable Permit real-world evaluation	Accuracy limited by sensor movement, drift, electrical interference, clothing, body habitus, activity
Smartwatches and smartphones	Accelerometer	Easy to use Portable Permit scalable real-world evaluation	Can be expensive in some cases Access may vary

Abbreviations: 3D = three-dimensional; GRF = ground reaction force; IMU = inertial measurement unit; mocap = motion capture.
Available motion analysis methods/devices, their strengths, and limitations.

patterns and expected gait analysis parameters are summarized in Table 3. In patients with complex multifactorial gait disorders, where a constellation of neurologic, orthopaedic, and systemic factors may be at play, gait parameters should be interpreted in the context of a careful medical history and detailed physical examination. Supportive tests such as neuroimaging or biofluid biomarkers may be needed to determine the underlying etiology.

Implications for Clinicians and Researchers

Digital Mobility Outcomes

Gait analysis is increasingly being used to quantify physical function as an outcome measure in interventional trials, often referred to as digital mobility outcomes (DMOs)[22]: rater-independent, objective measures of gait and balance that can be used for diagnostic support and monitoring of disease progression and response to therapies. DMOs have also paved the path toward remote monitoring of gait and balance in the free-living environment, allowing for better ecological validity.[5,23] In an analysis of ClinicalTrials.gov, a 39% increase in the use of digital technologies in clinical trials for neurologic diseases occurred between 2010 and 2020.[5] Objective outcomes captured remotely can increase accessibility, decentralization, and feasibility of clinical trials, especially for rare diseases.

When applying DMOs to a specific patient population, it is important to evaluate the clinically meaningful effect size; relationship with functionally relevant outcomes (e.g., falls and gait aid use); device, patient, and environmental factors. For example, for tracking disease progression, devices and analytical methods should remain consistent, and any device-related error should be smaller than the minimally clinically significant change in the gait parameter for a given disease. Consistency in methodology (data collection and analysis) across cohorts and studies is needed for generalizability of results. However, it is important to note that distinct gait parameters may be required to capture heterogeneous deficits across diseases that affect gait and balance differently. Hence, disease-specific recommendations regarding the most clinically relevant parameters will be key.

Methodology: Device, Data, and Experimental Design

Many existing studies using objective gait analysis accomplish disease detection by comparing clinically defined disease groups with normal controls. While this is a good first step to

Table 3 Features of Neurologic Gait Patterns

Gait pattern	Clinical phenotype	Key gait analysis features
Typical parkinsonian gait	Slow, short shuffling steps, dampened heel strike, reduced foot elevation, turn in multiple small steps, instability	Slow velocity, reduced step/stride length Narrow step width Static and dynamic instability, reduced ROM at multiple joints
Atypical parkinsonism	More prominent early onset of postural instability and falls along with other features of parkinsonism	Quantitative measurements may reveal a more substantial deficit than PD Slow velocity, reduced step/stride length Increased double support time due to instability Wide step width Early severe static and dynamic instability
Ataxic gait	Wide-based, unsteady, inconsistent foot placement, unable to walk with feet in tandem	Increased variability of spatial-temporal parameters Wide step width Static and dynamic instability
Hemiparetic gait	Unilateral weakness leading to foot drag, steppage, spasticity	Asymmetry of spatial temporal measures, reduced ROM, abnormal kinematics, reduced velocity, step/stride length, and single-limb support time on the affected side
Dystonic gait	Stiff-legged appearance, abnormal involuntary posture at rest or during walking/running	High-amplitude agonist-antagonist co-contraction on sEMG, abnormal kinematics in the affected limb, asymmetric spatial-temporal parameters
Spastic gait	Stiff-legged appearance, hyperextension at knees, hyperadduction of legs, brisk reflexes, clonus	Affected limbs may demonstrate diminished forces and ROM Slow velocity, reduced step/stride length, and support time on affected weak side
Neuromuscular disorders	Myopathy (proximal weakness): waddling Trendelenburg sign Neuropathy or MND (distal weakness): foot drag, steppage gait	EMG abnormalities Diminished motion and forces on kinematics and kinetics Slow velocity, reduced step/stride length Static and dynamic instability
Functional gait disorders	Variable abnormality, distractibility, inconsistent with known neurologic diseases, exaggerated or energy inefficient patterns of gait	No consistent diagnostic pattern of abnormality. Noted findings may be inconsistent and distractable

Abbreviations: MND = motor neuron disease; PD = Parkinson disease, ROM = range of motion; sEMG = surface electromyography.
Neurologic gait disorders and their characteristic clinically observed patterns and expected gait analysis features.

characterize abnormalities of gait and balance in a disease, it is rarely a clinically relevant question. Future opportunities to leverage gait analysis should include augmenting clinical diagnosis by evaluating early preclinical populations to predict phenoconversion, differentiating clinically overlapping diseases, and developing sensitive, disease-relevant outcome measures for tracking progression.

To accomplish this, reproducible methodology is important. Currently, the large and rapidly growing body of literature on gait analysis in neurologic diseases uses a range of measurement devices (wearable sensors, video-based mocap, pressure walkways, or smartphones), experimental designs, and data analysis software/algorithms. Validation of devices and software to understand sensitivity, specificity, accuracy, and reliability, and the use of sensor fusion algorithms to develop disease-specific best practices for gait assessment, will allow better comparability of findings across cohorts and studies.

Similarly, experimental design and tasks used to assess gait and balance may yield different results. It is critically important to determine best approaches to answer specific questions. For example, cognitive-motor dual-task vs single-task conditions, or walking assessed at self-selected walking speed, brisk walk, or treadmill testing at an artificially fixed speed, may serve different purposes but also affect comparability across studies.

Remote Monitoring

One of the most attractive goals of gait analysis is real-world or remote assessment of gait and balance to provide an objective assessment of function in the free-living environment. This can be accomplished in various ways; sending research or clinical-grade devices (accelerometers or IMUs) to participants to record data, which are then mailed back for data download and analysis; transmission of data in real time using a mobile application and cloud-based servers; or retrieving data from consumer-owned devices such as smartphones and smartwatches.

Medical/research-grade devices are more likely to be accurate but are more expensive, and the burden of mailing devices back and forth may affect compliance and scalability. In comparison, consumer-grade or participant-owned devices may be more easily integrated into day-to-day life, but depending on the device, available data may be limited, privacy concerns exist, and parameters measured by consumer-grade devices are often not validated. Compared with clinic or laboratory-based settings with a controlled environment and set protocols, remote monitoring requires additional

consideration of a range of external factors that may affect measurements (living environment, indoor vs outdoor time, physical activity level, body habitus, clothing, use of assistive devices or adaptive equipment, and how they interact with the gait analysis device). Depending on the study goals, concurrent activity tracking (diary or journal entries) may be required to put measurements into context but could add burden to the participant. Accuracy and reliability of measurements in the remote environment need to be assessed for any given device and disease group. Privacy of data also becomes a concern with any remote monitoring, especially with video or audio recording–enabled devices being deployed in homes and the need for secure transmission of data to the clinical or research team.

Artificial Intelligence/Machine Learning

Advanced computing capabilities allow us to gain insights from time-series gait analysis data using AI/ML algorithms.[3] For example, automatic detection of gait parameters or classification of pathologic gait using video data is possible through a variety of available open-source pose estimation models.[12,24] Specific abnormalities, such as gait freezing, can be detected automatically with a high level of accuracy.[25] Data-driven discovery can identify gait parameters that best characterize disease severity, heterogeneity, and detect subtle, or early changes in gait. Applications of this knowledge would include disease screening in early stages, such as in dementia and PD, for longitudinal monitoring of disease progression and as a clinical diagnostic support tool.[26]

Generalizability and validity of any AI/ML algorithm depend on characteristics of the data used for training, vs the test data to which it is applied.[27] Appropriate validation is required before applying an algorithm to a different data source or distinct population. Algorithms used vary widely, and at this time, insufficient data exist to develop best practice guidelines for data analysis of specific clinical/research questions. Data quality, internal and external validity of the algorithm, and clinical relevance of the findings are essential to consider. Data security and privacy are additional challenges for AI/ML systems in gait analysis. Data originating from gait analysis are often directly identifiable if video is used; however, in some situations, gait parameters are also considered biometric. For example, the Illinois Biometric Information Privacy Act regulates collection and storage of biometric information, including gait recognition. More number of states are following suit and have classified "gait patterns and rhythms" as an identifiable biometric.[28]

Recent Advances and Applications of Gait Analysis in Neurologic Diseases

In this section, we review recent advances and applications of gait analysis technology to specific neurologic diseases.

PD and Atypical Parkinsonism

Gait analysis has been used to classify PD,[29] assess response to therapy[30] and novel interventions (robotics, virtual reality),[31] differentiate atypical parkinsonism, and categorize symptom severity.[32] In atypical parkinsonism, such as progressive supranuclear palsy, where gait and balance deficits are more severe, wearable sensors (IMUs) may differ in validity and reliability for certain parameters.[33] In normal pressure hydrocephalus, which may present with a parkinsonian and gait apraxia, ST parameters are most illustrative of gait change after CSF diversion procedures.[34] Gait initiation delay in parkinsonian conditions can be measured using the latency and amplitude of anticipatory postural adjustments. Anticipatory postural adjustments refer to the posterior and lateral shift of COP before the swing phase required to generate the necessary GRF that propels the forward movement.[35]

Gait analysis also has been used as an outcome in PD clinical trials. A digital motor score was included as a secondary outcome in the PASADENA trial of prasinezumab[36] and in a trial of ursodeoxycholic acid, where sensor-based gait analysis detected changes on some parameters while the clinical rating scale did not.[37] Noncontact technologies have also been explored for remote monitoring in PD, such as in-home radiowave device that can detect gait velocity, which correlates with disease severity and levodopa on-off state.[38]

Gait freezing is a sudden cessation of gait due to dysfunctional corticostriatal pathways and leads to a sensation of "feet being stuck to the ground" and is a challenging symptom of late-stage PD and atypical parkinsonism. Gait freezing is visually assessed during clinical examinations, and frequency and severity are reported using rating scales. In a laboratory setting, EMG has been used to assess the tremulous phenotype of freezing through changes in the frequency of EMG burst activity, called freezing index.[39] More recently, supervised or unsupervised ML approaches have been applied to IMU or video data to assess frequency and severity of freezing.[25] The third international Workshop on Freezing of Gait 2023 reviewed measurement of gait freezing and made recommendations.[40] The group suggested using 2 video cameras and 5 IMUs (bilateral foot, bilateral shin, and lower back) but concluded that the best algorithm to analyze data was yet to be defined.

Ataxia

Ataxic gait is seen in many disorders and is characterized by increased step width and high variability of ST parameters.[41] The Ataxia Global Initiative Working Group on Digital-Motor Biomarkers assessed a large body of literature on different gait and balance parameters to assess their relative performance in discriminating ataxia severity[42] and their correlation with SARA scores. They recommended protocols and parameters for objective quantification of gait abnormality in ataxia; suggested parameters include velocity, sway, variability, and truncal ROM.[17] The same group has also presented consensus guidelines on the use of smartphone-

based sensor data in evaluation of ataxia, directing attention to the value of objectively captured gait/posture, upper limb function, and speech function.[43]

In a post hoc deep learning analysis of video-based gait data from the clinical trial of Troriluzole for spinocerebellar ataxia, a measure of stability derived from tandem gait revealed significant improvement among drug treated individuals compared to placebo group at 48 weeks.[44] Gait analysis has been used to differentiate spinocerebellar ataxia subtypes and identify abnormalities in preclinical cases of FXTAS repeat expansion carriers based on subtle differences, and track progression over time.[45,46]

Multiple Sclerosis

Functional mobility is measured in MS using the Expanded Disability Status Scale, which is a 10-point ordinal clinical rating scale of progressive disability ranging from 0 (normal neurologic function) to 10 (death due to MS) in half-point increments. In the past 3 years, there has been a rapid increase in the use of gait analysis in MS research using wearable sensors, video cameras, smartphones, and 3D mocap for kinetic and kinematic analysis and to identify gait patterns.[47,48] Quantified metrics, especially ROM, postural sway, and ST parameters, under dual-task conditions seem more sensitive to change than clinical measures; can detect changes early in the disease that may not be otherwise evident[49,50]; and help track subtle progression.[51] Objective gait parameters are being used primarily as exploratory outcomes in MS clinical trials evaluating drugs, noninvasive brain stimulation, and rehabilitative gait and balance, but a consensus on most relevant measures is needed.[52]

Neuromuscular and Peripheral Nerve Disorders

Neuropathy, most often diabetic but also from other causes, is a common source of gait impairment. Other than overall functional assessment using ST parameters, specific applications of gait analysis in neuropathy focus on joint ROM limitation from proprioceptive deficits or Charcot joints, resulting impact on balance,[53] and the use of GRFs and muscle activity to predict pressure ulcer development.[54] Remote gait analysis capturing stride speed and number per day has been shown to be a sensitive outcome measure in a clinical trial of muscular dystrophy,[55] and walking speed was a marker of amyotrophic lateral sclerosis progression and transition to use of gait aids.[56] Quantitative muscle strength testing using dynamometers (as opposed to manual muscle testing) can be an important adjunct to gait analysis in neuromuscular diseases that cause weakness, to quantify deficits and identify their source.

Stroke

Asymmetry in ST parameters, trunk and lower limb ROM, and kinetics, as well as dynamic and static balance, have been used to quantify stroke deficits. Wearable sensors and mocap have been used to quantify these parameters; assess the overall gait pattern, volume of physical activity, and postural stability; and estimate neuromuscular weakness such as foot drop.[57] Gait parameters have been used as outcome measures in clinical trials of rehabilitative interventions to enhance post-stroke motor function (vestibular, motor, and cognitive-motor dual-task gait training; noninvasive brain stimulation; virtual reality, exoskeleton, or robot-assisted physical therapy) and reveal greater efficacy of virtual reality–based training for dynamic balance compared with treadmill walking alone.[58]

Conclusion

Gait analysis can provide objective measurements of human gait and balance function, which is increasingly important for clinical care and translational research in neurologic disorders. Patient-centric DMOs can augment clinical diagnosis, evaluation of response to therapy, and longitudinal monitoring. The precision and accuracy of data depends on the device, analysis method, and patient and environmental factors. Heterogeneity in methodology across published literature exists, and evidence is specifically limited for validity of wearables for in-home assessments. For comparability of findings, identification of standardized parameters and appropriate validation of analytical methods (software and device) are important. AI/ML offers unique opportunities to make data-driven discoveries from large cohorts. However, careful consideration of data quality, internal and external validity of the algorithm, and the clinical or research application are essential. Data safety and patient privacy are of paramount importance and should always be considered when developing clinical or research applications of digital gait analysis.

Author Contributions

F. Ali: drafting/revision of the manuscript for content, including medical writing for content; major role in the acquisition of data; study concept or design; analysis or interpretation of data. H. Padilla: drafting/revision of the manuscript for content, including medical writing for content. A.M. Blazek: drafting/revision of the manuscript for content, including medical writing for content. L. Barnard: drafting/revision of the manuscript for content, including medical writing for content. K.R. Kaufman: drafting/revision of the manuscript for content, including medical writing for content.

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