Gait analysis in neurological populations: Progression in the use of wearables

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Abstract

Gait assessment is an essential tool for clinical applications not only to diagnose different neurological conditions but also to monitor disease progression as it contributes to the understanding of underlying deficits. There are established methods and models for data collection and interpretation of gait assessment within different pathologies. This narrative review aims to depict the evolution of gait assessment from observation and rating scales to wearable sensors and laboratory technologies and provide limitations and possible future directions in the field of gait assessment. In this context, we first present an extensive review of current clinical outcomes and gait models. Then, we demonstrate commercially available wearable technologies with their technical capabilities along with their use in gait assessment studies for various neurological conditions. In the next sections, a descriptive knowledge for existing inertial and EMG based algorithms and a sign based guide that shows the outcomes of previous neurological gait assessment studies are presented. Finally, we state a discussion for the use of wearables in gait assessment and speculate the possible research directions by revealing the limitations and knowledge gaps in the literature.

1. Introduction

Gait, the way a person walks, is one of the prominent functional activities that is needed to perform daily life routines [1] and maintain wellbeing [2]. Gait abnormalities due to underlying aetiology are among the most consistent predictors for falls [3] and abnormal gait can cause other severe consequences such as reduced life satisfaction and limited mobility [4]. Impaired gait is present in almost all neurodegenerative diseases. More than two-thirds of those admitted to hospital frequently suffer from a neurological condition that leads to a fall, where 85% of those patients were previously undiagnosed [5, 6].

Prevalence of neurological gait disorders increases from 10% (60-69 years) to 60% in those >80 years, where sensory ataxia and parkinsonism are the most prevalent disorders [7]. Generally, patients with neurological conditions show similar gait abnormalities, such as reduced gait speed, reduced step length and poor postural balance - suggesting common mechanisms that still need to be unravelled [8]. However, there are also subtle but characteristically nuanced patterns between different neurological conditions. Typical gait for ataxia includes hard foot strike on each step and staggering gait patterns [9, 10], while slow movement (hypokinesia) and loss of movement (akinesia) are common symptoms for Parkinson's disease (PD) [11, 12]. Post stroke hemiplegia causes severe disruption to gait, e.g. initially, 50% of the patients are unable to walk [13, 14] and for those who can, asymmetrical gait is common with a large variance in step length and step time [15, 16]. Other neurological disorders exist such as: Multiple Sclerosis (MS), a progressive and demyelinating disease of the central nervous system (CNS) that exhibits significant reductions in walking speed and step length due to deficiencies associated with ataxia, muscular weakness, spasticity and general fatigue [17, 18]; Progressive Supranuclear Palsy (PSP) is an uncommon degenerative neurological disorder resulting in decreased cadence and stride length and increased step with [19]. As each neurological condition seems to present nuanced gait characteristics, robust exploration of underlying impaired gait mechanisms and accurate measurement may play a vital role in targeted physical and/or pharmaceutical intervention. In this sense, impaired gait is assessed typically with traditional approaches (e.g. clinical rating scales) but more frequently with modern digital approaches.

Traditionally, patient assessment methods in supervised clinical settings have been widely performed by visual observation from a trained physiotherapist [20] utilising subjective rating scales, which rely on clinician expertise. The latter include but not limited to all or sections of: Unified Parkinson Disease Rating Scale (UPDRS) [21]; Scale for the Rating and Assessment of Ataxia (SARA) [22]; the Canadian Neurological Stroke Scale (CNSS) [23]; Alzheimer's Disease Assessment Scale (ADAS) [24]; or Expanded Disability Status Scale (EDSS) [25]; High-level Mobility Assessment Tool (HiMAT) [26]; Dynamic Gait Index [27]. However, there is ample evidence to suggest that clinical assessment scales may not be sensitive to disease severity and cannot evaluate specific characteristics [10, 20, 28, 29]. For example, shuffling gait in PD is difficult to assess from observation and subjective rating scores between patients lack clarity for robust comparison [28]. Consequently, the inability to collect standardised gait parameters from clinical rating scales under observation may limit understanding of underlying disease mechanisms which restricts robust monitoring of disease progression and tailored interventions [29].

Instrumentation of gait using different digital-based technologies provides information that is not possible to detect from clinical observation alone. The use of those devices in conjunction with clinical judgment, provides new insight on the dysfunction causing an individual's symptoms by providing objective digital gait characteristics [30]. These devices can be classified based on data collection protocols as non-wearable and wearable sensors where each has its own advantages and disadvantages [31]. Motion analysis systems, instrumented walkway systems and force plates/platforms have been pioneering non-wearable systems that are considered to be "gold/reference standard" for capturing kinetic, kinematic and spatiotemporal gait characteristics with reasonable to excellent accuracies [31, 32]. However, those technologies conform to a "one-size-fits-all" approach, meaning they are not applicable for individual phenotype or a particular condition, further limiting their use [28, 29, 31]. Additionally, those costly non-wearable systems require use of controlled research facilities and trained staff, which provide a snapshot assessment in optimal testing conditions within a predefined capture volume, e.g. length of an instrumented walkway. To overcome limitations of gait assessment in a controlled environment with limited time, home motion systems (e.g. Microsoft Kinect) that include cameras, infrared and radar-based devices have been used [33, 34]. Yet, when considering user feedback, security, limited data capture due to field of vision, these devices have limited use [35, 36].

Wearable technologies such as magnetic (e.g. magnetometers) and inertial measurement sensors (e.g. accelerometers and gyroscopes) and force sensors (e.g. insole foot pressure) have opened data capture opportunities that overcome limitations of non-wearable devices (e.g. continuous monitoring beyond the clinic). Magneto-inertial measurement units (MIMUs) have been used to reliably quantify the rate and intensity of movement by attaching to an

anatomical segment (e.g. leg, arm) to extract kinematic, temporal and spatial gait characteristics [37]. Alternatively, wearable foot pressure sensors (e.g. insole) have also been used to gather continuous kinetic gait characteristics (e.g. ground reaction forces, moments) [38, 39]. Wearable sensors enable gait assessment in a range of testing locations but of recent interest is during daily, free-living environments such as the home and in the community. In contrast to laboratory-based assessment, free-living gait assessment can provide continuous monitoring in real life (habitual) settings where natural dual-tasking or social interactions occur, which may provide new insights to neurological gait disorders [40].

To date, a plethora of digital gait outcomes have been extracted from various technologies and interpreted using different gait models and algorithms. This scoping narrative review aims to provide a comprehensive roadmap for the future development of neurological gait assessment by shedding light on limitations and knowledge gaps in existing methodologies and technologies, particularly wearable sensors. To achieve this, we aim to understand how gait is instrumented in section 2 by fundamental measurements, presenting clinical gait outcomes from conceptual models to determine current approaches. In section 3, we explore current-state-of-the-art for instrumented neurological gait with wearables by providing insight to their functionality along with correct attachment/placement protocols. Consequently, in section 4, we collate wearable-based (inertial measurement units (IMUs) and EMG) gait algorithms relating to gait phase detection for estimation of important gait parameters/characteristics and progress in section 5 to uncover how these have been used to define clinically useful outcomes for various neurological conditions. Finally, we discuss and conclude on current limitations and possible future directions of wearable technology in neurological gait.

2. Understanding gait: Clinical-based outcomes and conceptual models

Gait can be described as a cyclic pattern of body movements which advances an individual's position. Consequently, studying discrete gait cycles can provide nuanced and even personalised assessments. In order to analyse the gait cycle in detail, it is split into distinct time periods [41] where gait characteristics such as kinematic (e.g. hip, knee, ankle joints), kinetic (e.g. force, momentum) and muscle activation (e.g. force, onset - offset) occur with alterations during the gait cycle that can be extracted for sub-phase analysis [42].

2.1. Gait outcomes

2.1.1. Kinematic

The study of kinematics starts with the reconstruction of a body as a multi segment system using various technologies (e.g. motion analysis systems, inertial sensors). Digitally constructed body segments provide insightful knowledge about joint movements (e.g. joint angular velocity and acceleration) in 3D [30]. These 3D joint movements include rotations, flexions, extensions, abductions and adductions [43]. Typically, basic movements involved in human gait are (1) flexion and extension of the hip, knee, and ankle joints and front part of the foot; (2) abduction and adduction of the hip joint and (3) rotation of the hip and knee joints [44]. Furthermore, movements of the centre of mass (CoM) of each body segment impact overall body CoM, which is found critical for balance and energy expenditure [45].

2.1.2. Kinetic

Kinetic information consists of a set of insightful measures from force and momentum perspectives [46]. One useful kinetic outcome is ground reaction force (GRF), typically measured with force plates, instrumented treadmills or wearable pressure sensors (e.g. insole) during stance phase (foot is in contact with the ground) [47]. GRF may be distinctive in patients with a neurological condition, e.g. PD patients who experience shuffling walking may experience decreases in progression force and the second peak of vertical force [48]. Other useful kinetic outcomes include centre of pressure (COP), highly useful for postural balance assessment and; plantar pressure distribution of the foot, which contributes to understanding foot contact with the ground (force per unit area) [49-51]. The latter may help differentiate patients who demonstrate neurological gait patterns since neurological groups typically touch the ground with the entire foot unlike healthy comparisons [52]. The integration of kinetic (GRF, COP) and joint kinematics allow us to calculate joint moments, which is helpful to understand how external forces (e.g. GRF) interact with internal forces (e.g. muscle) to stabilize the joints [30].

2.1.3 Muscle activation

Normal gait relies on selective timing and intensity of responsible muscles at each joint [52]. Thus, investigation of the phasic contribution of muscles in a gait cycle is important [53, 54]. Highly informative muscle related outcomes (e.g. muscle onset and offset times, muscle synergies) have been used to investigate when the muscle fires, how muscle forces

change and what muscle synergies are responsible for walking [55]. Onset and offset time of muscle activations show the duration of active muscles during gait and are useful to diagnose abnormality in muscle coordination or altered muscle activity during freezing episodes in PD [56]. Additionally, motor unit action potentials (MUAP) provide insightful knowledge for the diagnosis of neuromuscular disorders since a raw muscle signal consists of super positioned MUAPs [57]. Amplitude, duration and number of phases are factors that characterise MUAP [58], where increased MUAP amplitude is associated with loss of muscle fibres [56]. Identification of muscle synergies during gait shows the coordinated recruitment of a group of muscles and help to understand how the CNS regulates these muscle synergies during walking [55]. Synergy vectors from healthy subjects can be compared with a group that suffers from a neurological condition using statistical correlation methods (e.g. Pearson correlation) to monitor similarities and alterations [59] (section 4.2).

2.1.4. Temporal and spatial outcomes

Temporal and spatial features are a common set of gait parameters since these are essential for the identification of more pragmatic gait characteristics. Typically, extraction of temporal and spatial outcomes starts with the identification of heel strike/initial contact (IC) and toe off/final contact (FC) within the gait cycle. A gait cycle can be described with swing and stance phases, which comprise approximately 38% and 62 % of the gait cycle for healthy adults, respectively [60]. Swing phase duration (i.e. swing time) is a temporal/timed measure when the foot under consideration is not in contact with the ground, which changes to stance phase duration (i.e. stance time) when the same foot contacts the ground [61]. Useful outcomes stemming from those timed durations include single limb support and double limb support, which have been useful to examine knee joint impairments [62] and balance control during gait [63], respectively. Spatial measures (e.g. stride length, step length) have been used to identify small steps and shuffles of impaired gait [28] while the more technically challenging outcome of step width (from wearables) is associated with base of support and postural balance [28]. Mathematical approaches for the estimation of temporal and spatial outcomes using wearables are explored in section 4.1.

2.1.5 Frequency and time-frequency outcomes

Typically, frequency domain analysis of acceleration signals allows investigation of how the signal's energy is distributed over a range of frequencies. Time-frequency domain analysis can answer the question when (in time) a particular frequency component occurs. Frequency-based measures are a valid and sensitive estimator of stride to stride variability that can be used to assess neurological conditions [64]. For instance; width and dominant frequency in acceleration epochs were linked to variability of gait domain where dominant frequency reflects average step time while the width is associated with the variability of the acceleration signal [65]. Furthermore, the bandwidth and energy concentration of an acceleration signal in the Medio-lateral direction have been used to discriminate impaired gait. For example; PD patients can be discriminated from healthy subjects (HS) as the former have larger bandwidth and lower energy concentrations [66]. Clinically, frequency and time-frequency outcomes are novel for use in neurological gait assessment compared to temporal and spatial outcomes where interpretation of the former remains subject to further investigation to inform pragmatic insights to neurological gait.

2.2. Conceptual models

Due to the redundancy of parameters and covariance amongst characteristics, conceptual gait models and classification approaches based on different technologies are proposed for ease of interpretation. Here is a non-exhaustive description of each stemming from creation in non-wearable to wearables;

1. Lord et al. developed a model consisting of 16-gait characteristic across 5 domains utilising non-wearable (instrumented walkway) outcomes and factor analysis with healthy older adults (69.5 years). The developed model is composed of (i) *pace* (e.g. step velocity), (ii) *rhythm* (e.g. step time), (iii) *variability* (e.g. step velocity variability), (iv) *asymmetry* (e.g. step-swing time asymmetry) and *postural control* (e.g. step width) [67]. The model was validated using a multimethod approach that included the replication of a previous work [68].
2. Hollman et al. proposed a gait model that consists of 23 gait parameters extracted from non-wearable (instrumented walkway) data for healthy adults (>70 years). This model also consists of 5 domains: (i) *rhythm* utilises temporal parameters such as cadence and stride time; (ii) *phase* consist of swing, stance, single and double support with % gait cycle (GC); (iii) *variability* includes numerous parameters such as variability of stride length and stride speed; (iv) *pace* includes gait speed and; (v) *base of support* consist of step width and step width standard deviation [69].
3. Sejdic et al. studied 17 parameters of healthy adults (65 years) and PD group (>65 years) using a motion capture system and a single wearable attached to lower back in clinical conditions. The extracted parameters are based on

5 different features; (i) *stride interval features* (e.g. gait speed), (ii) *statistical features* (e.g. standard deviation, skewness), (iii) *information-theoretic features* (e.g. entropy rate), (iv) *frequency features* (e.g. peak frequency, spectral frequency) and (v) *time-frequency features* (e.g. wavelet entropy) [66].

4. Morris et al. proposed a new model adapted from previous model (Lord et al.) for use with wearable data from older adults (mean age 69 years) and those with PD (mean age 72.3) during free living, which resulted in 14 gait characteristics across 4 domain [70]. The model defining: (i) *pace* (e.g. step velocity, step length), (ii) *rhythm* (e.g. step, stance, swing time), (iii) *variability* (e.g. variance of step, stance, swing time), *asymmetry* (e.g. asymmetry of step, swing, stance time).
5. Morris et al. upgraded previously proposed models by combining pace and turning gait characteristics in the same domain using six inertial sensors for a PD group (mean age 67.6). The developed model contains gait and balance components; each has four different domains. Gait model; (i) *pace & turning* (e.g. gait speed, stride length), (ii) *rhythm* (e.g. stride time, stance time), (iii) *trunk* (e.g. trunk coronal /sagittal/ transverse range of motion) and (iv) *variability* (e.g. standard deviation of stride length and stride time). Balance model: (i) *area & jerk* (e.g. sway area, JERK and Root Mean Square (RMS) in AP, ML directions), (ii) *velocity* (e.g. velocity in AP and ML directions) (iii) *frequency ML* (e.g. frequency in ML direction) and (iv) *frequency AP* (e.g. frequency in AP direction) [71].
6. Horak et al. proposed a model based on the outcomes of the instrumented stand and walk test of healthy adults (mean age 66.6 years) and PD patients (mean age 66.4) using six wearables. Here, the postural balance domain (e.g. sway parameters) is more dominant compared to the previous models. The proposed model consists 6 domains with 30 measures; (i) *sway area* (e.g. mean distance, CoM range), (ii) *sway frequency* (e.g. mean frequency, jerk (the rate of change of acceleration)), (iii) *gait speed* (e.g. stride velocity, step length), (iv) *gait trunk* (e.g. peak trunk velocity), (v) *gait timing* (e.g. cadence) and (vi) *arm asymmetry* (e.g. arm asymmetry velocity) [72].
7. Weiss et al. suggested a model heavily depends on frequency domain outcomes of healthy adults (>50 years) and a PD group (>50 years) during uncontrolled (e.g. free-living) environment using a single wearable attached to lower back. In the validation study, (i) *temporal measure*; average stride time and (ii) *frequency measures*; stride time variability, dominant frequency (Hz), amplitude, width and slope were examined[64].
8. Stuart et al. proposed a gait model for chronic mild traumatic brain injury (mTBI) (mean age 39.56) using five wearables. Proposed method consists of 13 gait characteristics and four domains; (i) *variability* (e.g. standard deviation of double support time, stride length), (ii*) rhythm* (e.g. stride time, single support time), (iii) *pace* (e.g. gait speed, foot strike angle) and (iv) *turning* (e.g. turn duration and turn velocity) [73].

These models show how complex instrumented gait assessment is, with numerous characteristics spread across different domains. Inconsistencies between studies result in reduced clarity and confusion where some gait characteristics are evidenced in different domains due to e.g. wearable placement and calculation of the same type of outcome (section 4.1).

3. Instrumenting gait

3.1. Reference standard technologies

Acquisition of quantitative information about the mechanics of the musculoskeletal system while executing motor tasks is a crucial phase of human movement analysis [74]. The following technologies are usually described as reference standards when comparing to wearable technologies.

Motion capture systems (also known as `mocap/mo-cap`): Motion capture systems can be classified as marker-based and marker-less systems. The former system uses retro-reflective markers along with a video-based optoelectronic system and various models (e.g. Newington model) to calculate the displacement of attached markers. Limitations such as the need for additional hardware (e.g. reflective markers, `mocap` suit) and time-consuming setup preparation drove researchers into developing more pragmatic marker-less systems, where conventional cameras are used together with various three-dimensional human models. Positioning performance of a common motion analysis system (Vicon Motion Systems Ltd, Oxford, UK) was studied. The accuracy of displacements with certain errors for dynamic and static experiments was investigated and favourable results were reported [75]. Motion analysis systems have been used successfully to obtain kinematic data in terms of joints (e.g. hip, knee, ankle) excursion and spatiotemporal parameters (e.g. step time and velocity) [76]. In-depth details on these systems are provided elsewhere [77, 78] but although they offer higher accuracies compared to other well know reference standards, their high costs and need for large space prohibit their use by researchers and clinicians.

Force platform technology (also known as force plates, FPs): Measure GRF, moments and COP using pressure sensors and load cells. FPs have been widely used to understand how movement is produced and maintained [79] but are limited to single foot strikes due to their small dimensions. Alternatively, instrumented treadmills or pressure mats/walkways (using an array of pressure sensors) can detect repeated footfalls. Performance assessment of instrumented treadmills for measurement of kinematic gait characteristics was studied as a result of a comparison with video-based system and results suggested that instrumented walkways provide comparable results for temporal parameters and further investigation is needed to evaluate the fidelity of its spatial performance [80]. Moreover, although instrumented walkway systems are widely accepted as the gold/reference standard, they are not without error[81]. In the validity studies, various technologies (e.g. clinical stride analyser) were used for validation of instrumented walkway systems and 0.51 cm and 0.67 cm mean absolute errors were reported for step length and stride length, respectively [32, 82].

3.2. Wearables for gait assessment

Wearables comprise a range of sensing technologies but the most popular comprise inertial-based devices where proposed use of acceleration signals for human movement date from the 1970s [83]. Developments in micro-electromechanical system (MEMS) and rise of validation studies have enabled inertial-based wearable technologies to replace the perceived reference standards by providing equally or more useful information with many advantages (e.g. easily accessibility, low cost, use beyond the lab) [49]. Yet, other wearable devices involving force sensing technology remain useful but creation of miniature data capture platforms have enabled new sensing capabilities. Examples of some commercially available wearables with numerous sensing capabilities are provided in Table 1.

3.2.1. Magneto-inertial measurement units (MIMUs)

MIMUs comprise magnetometers, accelerometers and gyroscopes, which are capable of capturing data across a spectrum of sensing properties (e.g. flux, velocity, acceleration, orientation, gravitational forces). Accelerometers are perhaps the most popular gait assessment sensor, which can measure 3D linear accelerations and have been used to detect initial-final contact (IC-FC) events to quantify temporal and spatial outcomes. Gyroscopes with their capability of measuring 3D angular velocities aid detection of body/segment rotation (e.g. turns). Magnetometers, are often used to increase the sensing capabilities of accelerometers and gyroscopes [84] with sensor fusion techniques due to their capacity of measuring direction, strength, and change of a magnetic field at a specific location [85]. Although accelerometers and gyroscopes could be used in isolation for gait assessment, a combination of these sensors together with magnetometers and additional features (e.g. wireless data transmission) produce a highly efficient system for reconstruction and analysis of in vivo locomotor system kinematics during gait [37]. Several reasons can be listed for preference of MIMUs in human movement analysis. Firstly, accelerometers and gyroscopes are self-contained during operation and can be used to collect quantitative motion data regardless of time and environment, and the ubiquitous presence of a magnetic field on earth makes it possible to use magnetometers in most locations [86]. Secondly, commercially available MIMUs are small, lightweight, and with additional hardware (e.g. Bluetooth, Wi-Fi, SD card), can gain useful features such as wireless data transmission or internal memory recording - facilitating easy data collection without affecting the natural movement of individuals [43].

3.2.2. Accelerometers

According to Newton's second law, an object with a constant mass (kg) accelerates (m/s^2) in proportion to the sum of applied net force (N). Accelerometers are developed from this principle using different approaches (e.g. piezoelectric, thermal and capacitive). Accelerometers are highly configurable devices where their bandwidth or frequency response can be set through coupling filter capacitors. This is an important aspect of accurate sensing as bandwidth must include frequency or vibration of the motion of interest. Range ($g = 9.81\ m/s^2$) and sampling frequency (f_s, Hertz, Hz) are additional parameters of interest that need to be selected considering the type of activity to be measured [87].

Dynamic range of an accelerometer is ± maximum amplitude that can be measured before distorting the output signal during data collection. Low intensity movement (e.g. postural balance) are assessed more sensitively with lower g values. Alternatively, high insensitive movements (e.g. gait) are accurately assessed with higher g values to capture high amplitude (range) movement without distorting or clipping. Most accelerometer-based wearables have selectable ranges; however, the optimal range depends on both the type of the movement and the body part making the movement. For example, 3D linear accelerations recorded at joints ranges from 3.0 to 12.0g, while lower back vertical acceleration and horizontal acceleration ranges from -0.3 to 0.8g and from -0.3 to 0.4g, respectively [88]. Thus, accelerometers must be capable of measuring accelerations up to ±12g regardless of attachment location but with enough resolution to capture subtle (low g) movement [89-91]. Additionally, f_s needs to be set considering the type of movement to be measured but

must also be considered for pragmatic reasons, high sampling rates negatively impact battery life [92]. Antonsson and Mann reported that during barefoot walking, 99% of the acceleration signal is contained frequency below 15Hz [93]. Similarly, Aminian et al. found that there was no significant acceleration frequency component above 16Hz at the lower back or the heel during treadmill walking [94]. Sun and Hill also found that the major energy band for daily activities (e.g. walking) ranges from 0.3 to 3.5 Hz [95]. Considering the findings of previous studies, Bouten et al. concluded that in order to assess daily physical activity accelerometers must be able to measure frequencies up to 20Hz [91]. Combining this knowledge with Nyquist theorem ($f_s > 2f_{max}$) where f_{max} is the max frequency component, preferred sampling frequencies ranged from 22–320 Hz [96], 50–1000 Hz [89] and 32–128 Hz [90] in previous gait studies where it seems 100 Hz is optimal, to capture adverse events during daily living, e.g. falls. In-depth description for accelerometer use in generic human movement analysis is found elsewhere [97-99] and details on post processing methodologies can be found in [99].

3.2.3. Gyroscopes

Gyroscopes measure angular velocity (°/s), are the next most widely used inertial sensor after accelerometers [100]. During deployment, scale factor stability, representing the sensitivity of the optical gyroscope, must be considered. A minimum scale factor stability leads small sensor errors and can be expressed by angle random walk (ARW) = R / [60sqrt(B)], where R and B represent resolution and bandwidth, respectively [101, 102]. A combination of tri-axial accelerometer and tri-axial gyroscope can deliver relative heading/direction, but the output drifts overtime.

3.2.4. Magnetometers

Magnetometers measure direction, strength and change of a magnetic field (Gauss) at a specific location. Specifically, magnetometers are sensitive to Earth's magnetic field and can be used to correct drift or for the detection of rotations in a known direction [85]. In the absence of magnetometers, 6 axes (accelerometer and gyroscope each in three axis) delivers relative heading, but with drift. Supplementing with magnetometers can solve drift by providing (absolute heading) a global reference point of the Earth's magnetic field [103]. However, magnetometers can be affected by localised magnetic fields, which may vary in uncontrolled environments (e.g. free-living). Given the popularity of accelerometer and gyroscope-based devices, the remainder of this text will focus on those only, inertial measurement units (IMU).

3.2.5. Pressure (force sensors)

Pressure and force sensors (e.g. insole) are the cornerstone of gait analysis and typically used to measure kinetic ground reaction forces (GRFs), temporal and spatial outcomes [104, 105]. These sensors transform the pressure information into digital current or voltage data. Capacitive, piezoelectric and piezo resistive types are the most commonly used underfoot sensors [31]. Estimation of GRF can be explained by Newton's third law; the plantar surface produces a vertical force in the direction of the ground, in response, another force in the opposite direction with the same intensity is generated [106]. Alternatively, gait events initial-final contact (IC-FC) can be detected using pressure sensor data, then spatiotemporal measures can be calculated from detected IC-FC in conjunction with simple mathematical equations. Recently developed foot pressure sensors provide plantar pressure profiles with visual feedback (e.g. pressure sensor map) [107].

3.3. Electromyography (EMG)

EMG sensors record myoelectric signals (i.e. motor neuron) using different electrode types (i.e. needle or surface). Needle (fine wire) electrodes are inserted into the muscle to detect neuromuscular abnormalities, while surface electrodes are used to record muscle activities by placement on the skin. Although the former provides more reliable outcomes, the invasive nature limits use. Surface EMG electrodes (sEMG, which have wireless options) offer more pragmatic opportunities with a non-invasive setup to record muscle activities in clinical and/or free-living environments [108].

Myoelectric signals are generally at the millivolt (mV) level and range from 10–1,000 Hz. For example; a muscle contraction can generate signals around 10Hz as a result of tissue displacement and whereas ground impact during walking produce 25–30 Hz signals [52]. As the EMG signal has low signal reception, it is more susceptible to unwanted signals (i.e. noise) mostly derived from tissue motion and neighbour motors. However, these noises are detected and eliminated at certain levels during signal acquisition and post-processing. During signal acquisition, unwanted electronic signals including common mode signal, which is a noise that flows in the same direction in a pair of lines (e.g. two surface electrodes), can be eliminated using differential amplifiers or instrumentation amplifier (IA), which has large common mode rejection ratio (CMRR) [52, 109]. For post processing noise reduction, digital low pass, high pass or band pass filters are used considering the sEMG frequency spectrum [110]. Scientific recommendations by the International Society of

Electromyography and Kinesiology (ISEK) and Surface EMG for Non-Invasive Assessment of Muscles (SENIAM) project suggest use of band pass filters with 10Hz low cut off and 500Hz high cut of frequencies to reduce aliasing (noise) effect when using an sEMG with a sampling frequency of 1kHz [56]. The major disadvantage of sEMG is cross talk, an incident that can be expressed as recording activities of neighbour muscles other than the muscle of interest. Muscle cross-talk is more likely to occur in sEMG, but use of spatial filters based algorithm helps to reduce interferences [111].

Table 1. Examples of some wearable devices

Company	**Shimmer**		**Axivity**		**McRoberts**	**BTS Bio Engineering**	**Mc10**	**xSens**	**Micro Sensors. Big Ideas®**	**Delsys**	**Noraxon**
Product examples	*Shimmer 3 IMU*	*Shimmer3 EMG*	*AX3*	*AX6*	*Move Monitor*	*G-WALK*	*BioStamp RC*	*MTw Awinda.*	*Inertia-Link®*	*Trigno Avanti*	*Ultium EMG*
Size and weight (grams, g)	24.276 cm^3 23.6g	27.3 cm^3 31.0g	5.6 cm^3 11.0g	5.6 cm^3 11.0g	70.7 cm^3 55.0g	50.4 cm^3 37.0g	10.1 cm^3 7.0g	18.33 cm^3 16.0g	61.9 cm^3 39.0g	12.987 cm3 14.0g	14.95 cm^3 14.0g
Sensing capabilities	ACC. GYRO. MAG. PRES. TEMP.	ACC. GYRO. MAG. PRES. EMG ECG	ACC. TEMP. LIGHT	ACC. GYRO. TEMP. LIGHT	ACC. MAG. BAR. TEMP.	ACC. GYRO. MAG.	ACC. GYRO. EMG.	ACC. GYRO. MAG. BAR.	ACC. GYRO.	ACC. GYRO. MAG. EMG.	ACC. GYRO. MAG. EMG.
Range of ACC. (g)	± 2,4,8,16	± 2,4,8,16	± 2,4,8,16	± 2,4,8,16	± 2,4,8	± 2,4,8,16	± 16	± 16	± 2,5,10	± 2,4,8,16	± 16
Range of GYRO. (°/s)	± 250,500, 1000,200 0	± 250,500,10 00,2000	×	± 125,250, 500,1000 ,2000	×	± 250,500,1000 ,2000	± 2000	± 2000	± 75,150,300,600, 1200	± 250,500,1000,2 000	± 2000
MAG. (Gauss)	± 49.1	± 1.3-8.1	×	×	± 10.0	± 12.0	×	± 1.9	×	± 49.0	± 48.0
f_s (Hz) ACC.	10.24-1024	512	12.5-3200	12.5-1600	50-200	4-1000	15.6-250	20-120	1-250	24 - 473	4000
Memory	≤32 GB	≤32 GB	512 MB	1024 MB	1024 MB	256 MB	32 MB	×	×	×	2 GB
Battery life	≤69 hours @256 Hz	N/A	≤14 days @100 Hz	≤7 days @100 Hz	≤14 days	8 hours	3 days	6 hours	N/A	8 hours	8 hours
Each sensor #axes	3	3	3	3	3	3	3	3	3	3	3
Wıreless data transfer	×	✓	×	×	×	✓	✓	✓	✓	✓	✓

ACC.: Accelerometer, GYRO.: Gyroscope, MAG.: Magnetometer, PRES.: Pressure, TEMP.: Temperature, BAR.: Barometer, EMG: Electromyography

3.4. Validity

Validity (and reliability) of wearables for robust gait analysis of neurological conditions is crucial for clinic and free-living assessment and of great importance as the field matures. Recently developed expert opinion has a 3-way framework defined by (1*) verification*, (2) *analytical verification* and (3) *clinical validation* (V3) for biometric monitoring technologies [112]. According to the framework, *verification* entails systematic evaluation of sample level sensor outputs considering patient safety using various methods such as bench testing prior to patient use. The *analytical validation* stage translates the evaluation procedure for sensors from the bench to patient use. This stage mostly investigates how well the data processing algorithms that convert sample-level sensor measurements into physiological metrics and requires collaborative work between the engineering/computing team responsible for developing the sensor/wearable technology and the clinical team. *Analytical validation* requires a well-defined data collection protocol including the following information; type of system (e.g. inertial sensors used), the way the sensors attached (e.g. orientation and exact location) together with study population details. Finally, *clinical validation* evaluates whether the sensor acceptably identifies or measures clinically meaningful outcomes in a stated context of use, conducted by clinical teams who investigated including accuracy, precision and reliability within a specific patient population.

Often *verification* is a technical process that is not conducted in the literature. One example of bench testing for IMU sensor assessment in gait includes use of a pendulum to assess an accelerometer for its suitability to measure dynamic acceleration compared to an electronic goniometer [113]. Instead, various gold/reference standard technologies are used to conduct wearable *analytical* and *clinical validation* studies [114-118] in tandem, with no clear distinction between those processes. For these combined *analytical* and *clinical validations*, wearable outcomes and gold/reference standard systems are compared [119, 120] while the cohorts wear the IMU-based technology (for the first time), perhaps limiting insights to IMU or algorithm deficiencies for that group. Although each system (IMU, 3D motion and walkway) measure different components, systematic errors will always remain in practice [121]. Therefore, validation should be performed in a step-by-step approach where discrepancies and agreements should be investigated and reported, taking an acceptable rate of errors into consideration between V3 processes.

3.5. Wearable placement

3.5.1. IMU

Typically, IMU wearables are fixed on the skin with a strap or double sided tape. Although this method of attachment provides a wide range of informative parameters with a certain accuracy, this might create problems like relative movement (e.g. linear, angular) between IMU wearables and underlying bones due to soft tissue artefacts, displacement of the fixation clothes or strap [122]. Relative motion based on problems during data collection may cause a discrepancy, which can affect the accuracy and robustness of a developed algorithm. Therefore, attaching an IMU, taking into account the location of the soft tissues may provide more stable and reliable signal acquisition.

IMU locations have crucial impacts on algorithms (e.g. use of thresholds) since the characteristics of acceleration and angular velocity differ from one location to another. Moreover, the location of the IMU has a direct effect on the extracted parameters/outcomes. An extensive investigation for the effect of IMU locations on the extraction of different parameters for a neurological condition is presented elsewhere [123]. To date, most preferred sensor locations for gait assessment are the lower back (3^{rd} to 5^{th} lumbar vertebrae, L3-L5) or feet/foot. In many circumstances, whole body movement analysis with a single device is necessary; thus, IMU location as close as possible to the CoM (i.e. L5) is preferred [98, 124]. Various sensors and their locations for gait analysis in different pathologies is presented in Figure 1.

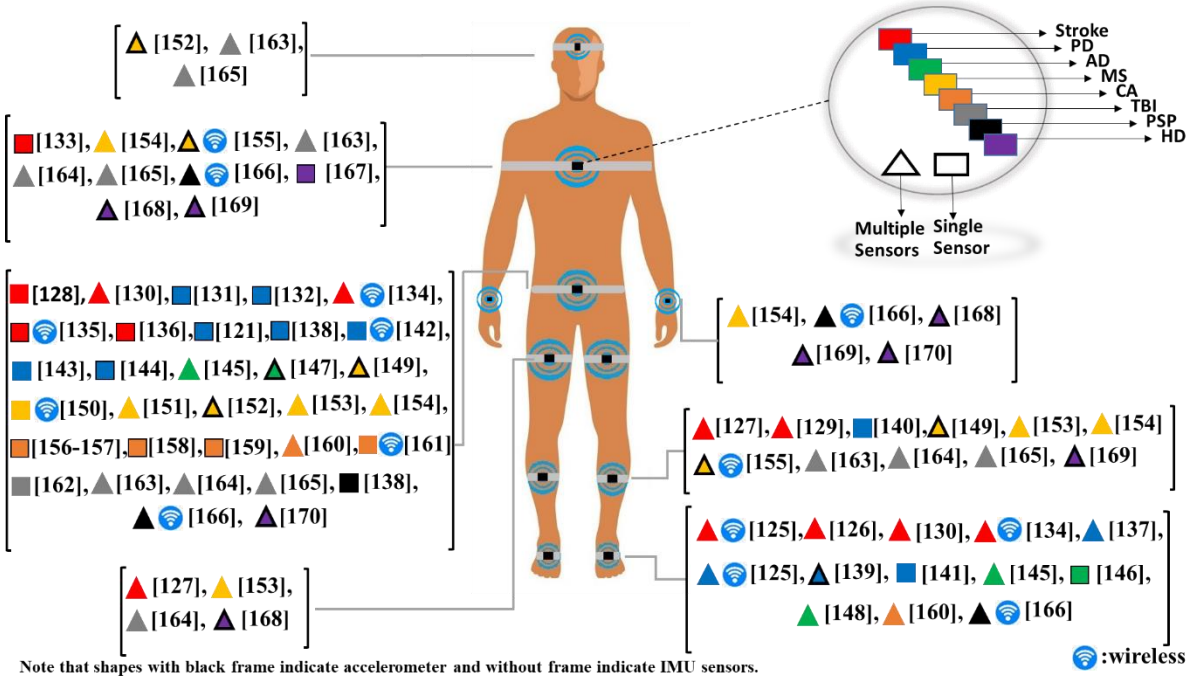

Figure. 1. Previously preferred sensor configurations and locations for different pathologies (PD: Parkinson's disease, AD: Alzheimer Disease, MS: Multiple Sclerosis, CA: Cerebellar Ataxia, TBI: Traumatic Brain Injury, PSP: Progressive Supranuclear Palsy, HD: Huntington's Disease)

3.5.2. EMG

Large discrepancies were observed in the previous EMG based studies in terms of electrode placement protocols. Mainly, targeted muscle groups and use of various types of surface electrodes such as different size and shape limit the standardization of EMG. To overcome these discrepancies and to offer guidance to the field, an atlas of muscle intervention zone [171] and SENIAM [172] were introduced. In those guides, electrode placement protocols typically include identification of electrode type such as shape and material, skin preparation, position of the patient, electrode location and fixation [173]. Further guides for sEMG placement can be found in [174, 175] but of note is that soft tissue or inappropriate muscle selection during sEMG measurement limits collection of meaningful data.

sEMG attached to lower limb muscle can provide reliable muscle activity and muscle force information for gait assessment of neurological conditions [176] where muscle activities of 28 major muscles controlling each lower limb can be readily identified [52]. In general, lower leg and foot muscles that are ideal for sensor placement include gastrocnemius medialis-lateralis, soleus, tibialis anterior, peroneus longus-brevis, with reference electrode location for sEMG at the ankle [173]. Following SENIAM recommendations, tibialis anterior, lateral gastrocnemius and rectus femoris muscles have been selected to collect EMG parameters (amplitude, variability) for gait assessment of PD [177]. However, we observed discrepancies in the muscle groups selected, probably due to the study of different neurological conditions. In the literature, few studies have taken into account the recommendation in the atlas guides during sEMG measurement. We found tibialis anterior and lateral gastrocnemius muscle groups [178] and rectus femoris, biceps femoris, tibialis anterior and gastrocnemius medialis [179] were selected to investigate muscle activities in healthy and pathologic groups. Figure 2 presents the electrode locations for different patient groups.

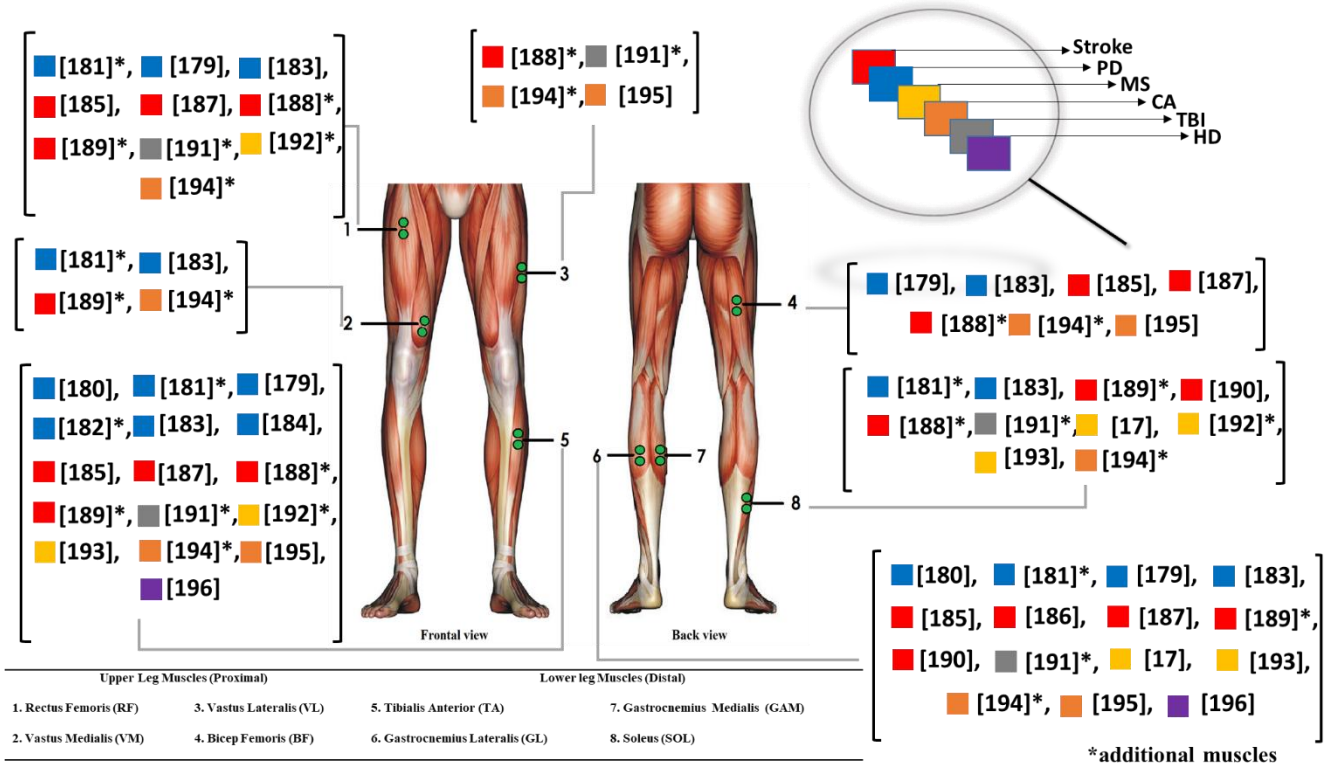

Figure.2 Previously preferred electrode locations for different pathologies (PD: Parkinson's disease, MS: Multiple Sclerosis, CA: Cerebellar Ataxia, TBI: Traumatic Brain Injury, HD: Huntington's Disease)

4. Gait algorithms

4.1. Inertial algorithms

Robust detection of IC and FC within an IMU signal draw upon timing sequences and mathematical formulae (supplementary material 1 and 2) once regions of interest from IMU signals are identified. Some methods for defining and examining those regions have been presented previously [197, 198]. Here, we include more recent algorithms:

1. (Lower trunk based) McCamley et al. proposed an algorithm based on a number of different signal processing techniques. Initially, vertical acceleration was pre-processed thorough Continuous Wavelet Transform (CWT) with Gaussian wavelet function, then IC events were detected as the times of the minima of the processed signal while FC events were detected as times of the maxima of the signal obtained after a further CWT differentiation [199].
2. (Lower trunk based) Zijlstra and Hof, proposed two different methods (zero-crossing and peak detection) that use the acceleration signal in AP direction to detect foot contact moment. After low pass filtering the forward acceleration signal with (4^{th} Butterworth 20 and 2 Hz cut off frequencies), (1) the switch from positive to negative was taken as IC. In a refinement of this method, the peak forward acceleration was taken as the instant of ICs. [200].
3. (Lower trunk based) Paper by Gonzalez et al. reported a comprehensive algorithm that uses filtered (11^{th} order, finite impulse response filter) acceleration in AP direction. In the algorithm, enclosed areas by positive values of the filtered signal, preceding for every zero crossings detected was approximately calculated. Then, the calculated areas were compared to the given threshold rates. When the calculated area is above the threshold rate, a search window together with a set of rules are used to locate the peak (local maxima) associated with IC event. Once the IC event is detected, incoming samples are processed searching for the first local minimum that identifies the FC event [201].
4. (Lower trunk based) Shin and Park suggested a step duration estimation algorithm that uses tri axis acceleration norm. Sliding window summing (SWS) was used to reduce the noise in the acceleration norm signal. As the SWS signal was sensitive to gravity, acceleration differential technique was also used to eliminate the effect of gravity.

Then, the obtained signals were processed to identify zero crossing moments that are associated with periodic steps [202].

5. (Lower trunk based) Köse et al. proposed a wavelet based approach that uses Daubechies wavelet due to similarity of IMU signals during gait. First, accelerometer signals were decomposed in an approximation curve and ten levels of details. Then, thresholds were applied, and signals were reconstructed using only the first three detail levels. In the following step, IC and FC were detected in the region of interest considering maximum and minimum points in different directions of accelerometer signals based on visual investigation [203].
6. (Lower trunk based) Yoneyama et al. proposed an extensive self-adaptive algorithm to detect the stride events and active rhythm blocks from an accelerometer signal attached to the lower back. The proposed algorithm consists of different analytical tools such as normalized cross-correlation, anisotropy, and biphasicity score, to process the 3-D acceleration signal and track long term gait monitoring. The algorithm aims to detect correct gait peaks [132].
7. (Lower trunk based) Bugané et al. proposed an algorithm to estimate spatiotemporal parameters using filtered (Butterworth low pass filter, 2 Hz cut off frequency) anteroposterior acceleration signals. From the typical acceleration curve with two positive and one negative peak, the second positive peak was taken as the instant of IC. To discriminate automatically between the left and right steps, the medial-lateral acceleration was analysed. Assuming the sensor was very close to the centre of mass (L5), acceleration to the left was taken as that during the right leg support phase and vice versa [204].
8. (Shank based) Trojaniello et al. proposed a gait event detection algorithm based on two MIMUs attached above the ankles. In the proposed algorithm, first trusted swing phase time interval (T_{SW}) was defined with thresholds and a set of rules applied to angular velocity in the sagittal plane. Then, ICs and FCs were searched in a time interval (T_{IC} and T_{FC}) which were considerably reduced by considering the estimated T_{SW}. IC was identified as the minimum value of the ML angular velocity occurring before the instant of maximum AP acceleration in the reduced time interval (T_{IC}). The FC was identified as the instant of minimum AP acceleration in the T_{FC}, since it is expected to occur at the time of a sudden motion of the shank preceding the instant of the last maximum AP acceleration value in T_{FC} [205].
9. (Shank based) Salarian et al. developed an algorithm to estimate gait events (IC and FC) using a gyroscope signal attached to shanks. First, mid-swing area (t_{ms}) was detected by applying a threshold (50 °/s), then local minima of shank angular velocity (IC) was searched in the interval of t_{ms} [t_{ms}-1.5s- t_{ms}+1.5s]. In the following stage, the signal was low pass filtered with 30 Hz cut off frequency and local minima with amplitude less than -20 °/s was searched to detect FC [206].
10. (Shank based) Aminian et al. proposed an algorithm to estimate initial-final contact (IC-FC) events based on shank angular velocity. First, wavelet decomposition (Fifth order Coiflet with ten scales) was used to split the signal into low and high frequency components. Then, the approximation approach was used to separate IC components and FC components. Global maximum values (mid-swing) were detected as a reference to detect IC and FC. In the following stage, IC- FC were detected by finding local minima inside of a pre-determined time intervals [207].
11. (Shank based) Catalfamo et al. developed an algorithm to detect IC-FC events from shank angular velocity. The determination of IC and FC events is based on the detection of two negative peaks in the shank angular velocity signal. The algorithm searches for the swing phase of the cycle which is detected when the gyroscope signal exceeds a threshold for another time threshold (40 ms). The first negative minimum after the swing is defined as IC. Then, FC event is estimated after defining a waiting time and a set of rules [208].
12. (Shank based) Lee et al. suggested a novel algorithm to estimate hemiparetic and normal gait parameters after detection of initial contacts (ICs) using 3 axis accelerometer. First, raw acceleration signals were filtered with Finite Impulse Response (FIR) bandpass filter and Least Square Acceleration (LSA) filter, respectively. Then, highest peak points and lowest valley points were detected from Anteroposterior, Medio lateral and Vertical accelerations. Finally, estimated step detection points were extracted after applying a set of conditions to the extracted the highest and lowest point of all axes [120].
13. (Shank based) Khandelwal and Wickstrom proposed a novel algorithm that efficiently identifies gait events from accelerometer signals using continuous wavelet transform (CWT). The ‘symlet-4’ (sym4) mother wavelet was chosen with 40-80 scale rates. Then, a rough envelope (RE) was obtained for both IC and FC events. K means clustering algorithm was used to differentiate IC (higher cluster) and FC (lower cluster) regions. Finally, IC and FC events were searched in relevant regions after the elimination of noisy IC-FC events [209].

14. (Foot based) Barth et al. developed a stride segmentation algorithm on the basis of the subsequent dynamic time wrapping technique. The developed algorithm uses gyroscope signal in the vertical axis from an IMU attached to foot to search similar points to the template. FC was detected with zero crossing while IC was detected by searching the minima between steepest negative slope and steepest positive slope. The mid stance was also detected considering the lowest energy point in all axes of gyroscope signal [210].
15. (Foot based) Chang et al. presented a gait phase detection algorithm that uses tri axis angular velocity of wearables attached to feet. First, signal vector magnitude (SVMag) was calculated from gyroscope data. Then, the slope of the SVMag and a sample timer was used to detect FC. The slopes of SVMag that are higher than the predefined threshold rate considered as FC events. In the meantime, another threshold was used for a timer to extract true FC events by avoiding the influence of the user's unconscious foot trembles and walking friction. Once, FCs were detected, each local maximum (peaks) within the interval of each two successive FC points were defined as IC events [125].
16. (Foot based) Hsu et al. proposed a partially similar algorithm to Chang et al. using SVMag approaches for foot mounted inertial sensors. Initially, SVMag of accelerometer and gyroscope signals were calculated. Windowing technique that segments SVMag signals into windows was used, then the variances of acceleration and angular velocity for each window were calculated. In the following step, the start flag was set, and the signals were scanned window by window. Then, starting points of the stride (IC) were detected when the variance of both acceleration and angular velocity of a window is higher than predetermined two different threshold values (one for acceleration and one for angular velocity). Ending points of stride (FC) were calculated with a similar approach but different thresholds [145].
17. (Foot based) Stamatakis et al. proposed an algorithm based on accelerometer attached to a foot. First, accelerometer signal was high pass filtered with 10 Hz cut off frequency, then peaks that represent ICs were detected as heel strike results in a high amplitude and frequency peak in the x-axis of the acceleration signal [139].
18. (Foot based) Chung et al. developed an algorithm that uses an acceleration signal of foot mounted sensor to detect starting and ending points of strides (also known as IC-FC events). First, signal vector magnitude (SVMag) of the 3D acceleration signal was calculated, then segmented into 3 sample window size. IC contact was detected by finding the first sample point after the variance of the SVMag window surpass the pre-determined threshold. Equally, once the variance of the SVMag is found lower than the threshold, first sample data was accepted as FC [146].
19. (Foot and shank based) Jasiewicz et al. developed three different algorithm using foot linear accelerations, foot sagittal angular velocity and shank sagittal angular velocity to identify IC-FC events of individuals with spinal-cord injuries. (1) IC-FC detection using foot linear accelerations; FC was identified by searching for a peak in forward-directed acceleration, within the FC search window located 250 ms before and 50 ms after each peak of ankle plantar flexion. To identify IC events, the algorithm searched for a vertically directed acceleration peak within the IC search window 100 ms before and 100 ms after peak ankle dorsiflexion. (2) IC-FC detection using foot sagittal angular velocities; To identify FC using foot angular velocity data, the algorithm searched for the first maximum in angular velocity in the FC window defined earlier. IC was identified as the velocity zero-crossing point in the IC window defined above. (3) IC-FC detection using shank sagittal angular velocities; The algorithm evaluates rapid changes in timing characteristics and selects the two minima on either side of a peak in velocity. The first minimum was associated with FC and the second minimum with IC [211].

We found few studies that robustly investigated and compared these gait algorithms, especially in clinical cohorts. Of those retrieved within the literature, one performed a comparative evaluation for accuracy of three methods (presented above *1-3*) using a single inertial sensor mounted on the lower back [199]. In a similar study, sensitivity and robustness together with accuracy of five different algorithms (*1-5*) for the estimation of gait temporal parameters were studied using a single inertial sensor mounted on the lower trunk in [212]. Findings of the study suggested that the accuracy in estimating step and stride duration for all methods were acceptable for clinical use but *1* was optimal. Moreover, the same study also investigated the robustness of the IMU positioning of three algorithms (*1-2* and *4*) for four different locations around the lower trunk, and algorithm *1* and *4* reported as highly robust.

4.2. EMG algorithms

Often, EMG sensors are used with additional systems since the identification of the gait cycle is challenging from EMG signals alone [181-183]. Some recent EMG based gait assessment studies, together with various technologies are presented in Table 2. When EMG signals arising from gait have been correctly identified, they have been used in conjunction with different signal analysis techniques (e.g. Fourier transform) or artificial intelligence techniques (e.g. fuzzy logic) to develop advanced EMG detection and analysis. These signal processing techniques and algorithms facilitate differentiation of neurological gait from healthy gait but also contribute to monitoring specific gait abnormalities [57]. The following are current approaches to analyse EMG data:

1. The linear envelope of an EMG signal is an easy-to-interpret representation of the raw signal as it gives an indication of the overall level of activity in a particular muscle at any time. Typically, the envelope of the raw EMG signal is extracted by means of a technique based on a full-wave rectifier followed by an integrator (smoothing filter) or RMS operation. D' Alessio et al. proposed an alternative method that improves the drawbacks of the traditional approaches by using an adaptive iterative procedure which automatically sets and dynamically changes length of the smoothing filter [213].
2. Figueroa et al. used a Kalman filter and unbiased finite impulse response (UFIR) filter to extract EMG envelopes and remove some artefacts with a maximum accuracy [214].
3. Micera et al. presented the characteristics of novel statistical algorithms and traditional approaches for detection of muscle activation intervals (on set and off set timings). Single and double threshold methods which compare EMG signal with predetermined thresholds are the most intuitive method for investigation of onset-off set durations of muscle contraction activity, studied in [215].
4. Paper by Otter et al. used a clustering algorithms to find similarities between EMG amplitude data points and grouped these data points according to their similarities to detect muscle activity/inactivity durations. The primary reason for using k-means is that it does not require a priori thresholds [216]
5. Ren et al. developed an algorithm based on single channel EMG recording for extraction of MUAPs. First, noises were removed through wavelet filtering and thresholds were estimated with wavelet transform. Then, MUAPs were extracted based on amplitude single threshold filtering. Finally, MUAPs were classified to detect active segments [217]. More algorithms are available for EMG decomposition into MUAPs in [56, 57].
6. Linear decomposition of multi-source EMG signal is another investigation methods that help to monitor the alterations in EMG characteristics of patients with gait disorders [218]. In this sense, muscle synergy approach has been widely used with a number of linear decomposition algorithms (e.g. principal component analysis (PCA), non-negative matrix factorization (NNMF)) to understand the physiologic aspects of gait disorders [56].
7. Frequency and time-frequency analysis of EMG data can be used to distinguish specific gait abnormalities by providing useful outcomes such as median power frequency (MdPF) and instantaneous mean frequency (IMNF) using signal processing techniques (e.g. fast Fourier transform (FFT), wavelet transform). FFT technique was used to compute power spectra, which is found distinctive in certain neurological conditions [56]. While IMNF which is the average frequency of power density spectrum of a signal found discriminative factor between affected and unaffected sides of stroke patients [219]
8. Power spectral density (PSD) provides useful information to understand which frequencies contain the signal's power and can be distinctive for some patient groups (e.g. PD) [220]. Go et al. computed the PDS using FFT (Welch method 50% overlap) and also calculated MdPF and total power of low frequencies to investigate the differences between muscle characteristics of dystonic and non-dystonic patient groups [221].
9. In recent years, classification of EMG signals has been the interest of many researchers. Different type of classifiers (e.g. ANN) has been used with a wide range of sEMG features (e.g. integrated EMG, mean absolute value, RMS) as detailed in a review [222].

Table 2. EMG approaches for gait assessment in some neurological disorders

Neurological Condition	Ref.	Device	f_s	Muscle of interest	Used together with to identify gait	Groups	# subject – (mean age)
PD	[180]	Delsys Trigno (Delsys Inc., Boston, MA)	4,000 Hz	TA-GL-GAM	Motion Analysis - (Vicon Nexus, Oxford, UK) Instrumented treadmill (Bertec Corporation, Columbus, OH)	PD HS	5-(57) 5-(27.6)
	[181]	Konigsburg Instruments, Pasadena, CA	1,200 Hz	SOL- GAM-VM-RF-TA-GM-SM	Motion Analysis- (Vicon Nexus, Oxford, UK)	PD HS	15-(66.6) 14-(66.2)
	[179]	TeleMyo 900, Noraxon USA, Inc.	1,000 Hz	RF-BF-TA-GAM	Motion Analysis -	Freezers Non-freezers	12-(69.1) 14-(66.1)
	[182]	K-Laboratory EMG system; The Netherlands	2,500 Hz	TA-GS	Motion Analysis-(Vicon Nexus, Oxford, UK)	Freezers	11-(64.8)
	[183]	EMG preamplifier SX230, Biometrics Ltd., Gwent, UK	1,000 Hz	RF-VM-TA-BF-GL-SOL	Motion Analysis-(Vicon Nexus, Oxford, UK)	PD	9-(76.6)
	[184]	TMSi Mobita, The Netherlands	2,000 Hz	TA	Foot switch – EEG(TMSi Mobita, The Netherlands)	PD HS	20-(67.4) 24-(65.1)
Stroke	[185]	MediTrace ECG 1801 Pellet	2,400 Hz	BF-RF-GAM-TA	Motion Analysis- (PRIMAS^{TM}	Stroke	14-(54.7)
	[186]	(SATEM Mygotron, SATEM srl, Rome,Italy	-	GL	Motion Analysis- ELITE (BTS, Milan, Italy)	Stroke HS	10-(61.6) (62.6)
	[187]	Noraxon USA Inc., Scottsdale, Arizona, USA	1,000 Hz	TA-GAM-RF-BF-	Motion Analysis- (Vicon Nexus, Oxford, UK) force plates (Advanced Mechanical Technology Inc., Watertown, Massachusetts, USA)	Stroke HS	35-(61.04) 9-(61.0)
	[188]	Noraxon, Inc., Scottsdale, AZ, USA	2,520 Hz	TA-GS-SOL-RF-VL-BF	Motion Analysis- (Inc., Santa Rose, CA, USA)	Stroke	5-(51)
	[189]	MA-416-003 Motion Lab System Baton Rouge, LA	2,000 Hz	TA-SOL-GAM-VM-RF-LH-MH-GM	Force Plate- (Bertec Corporation, Columbus, OH)	Stroke HS	34-(61.6) 20-(56.1)
	[190]	Motion Lab Systems MA300-28, Baton Rouge LA	1,000 Hz	SOL-GAM	Motion Analysis- (VICON, Colorado, USA)	Stroke HS	24-(62.7) 17-(70.1)
Traumatic Brain Injury (TBI)	[191]	Delsys Trigno (Delsys Inc., Boston, MA)	1926 Hz	TA-GAM-SOL-VL-RF-MH	Accelerometer – (Trigno Delsys Inc., Boston, MA)	TBI HS	44-(53.4) 20-(25.3)
Multiple Sclerosis (MS)	[17]	Noraxon Telemyo 2400T EMG system Noraxon, Scotsdale, AZ	1,200 Hz	GAM-GL-SOL	Motion Analysis- (Vicon Nexus, Oxford, UK) Force Plate- Kistler Instruments AG, Winterthur, Switzerland)	MS HS	16-(42.01) 10-(37.21)
	[192]	Tyco Healthcare Nederland BV, Zaltbommel, the Netherlands)	1,000 Hz	HS-RF-TA-SOL-GS	Motion Analysis- (Basler Pilot piA640-210gc GigE, Basler AG, Ahrensburg, Germany) Force Plate- (AMTI, OR6-5-1000, Watertown, Massachusetts)	MS	81-(47.1)

Neurological Condition	Ref.	Device	f_s	Muscle of interest	Used together with to identify gait	Groups	# subject – (mean age)
	[193]	(EMG) system Cometa, Milano, Italy	1,000 Hz	TA-GL-SOL	Motion Analysis-(Vicon Nexus, Oxford, UK)	MS	30-(42.5)
						HS	15-(36.8)
Cerebellar Ataxias (CA)	[194]	FreeEMG 1000; BTS SpA, Milan, Italy	1,000 Hz	GM-RF-VL-VM-SM-BF-TA-GAM-GL-SOL-PL- TFL	Motion Analysis- (SMART-D System; BTS, Italy, Milan)	CA	23-(50.0)
						HS	23-(48.4)
	[195]	EMG; FreeEMG300 System, BTS	1,000 Hz	VL-BF-TA-GAM	Motion analysis - (SMART-DX 500 System, BTS, Milan, Italy)	CA	13-(50.2)
						HS	13-(50.2)
Huntington Disease (HD)	[196]	Micromed Brain Quick- (Mogliano Veneto, Italy)	256 Hz	TA-GL	EEG- (Micromed Brain Quick, Mogliano Veneto, Italy)	HD	24-(48.13)
						HS	14-(48.8)

Semimembranosus (SM), gluteus medius (GM), peroneus longus (PL), gastrocnemius (GS), lateral hamstring (LH), medial hamstring (MH), hamstring muscle (HS), tensor fasciae latae (TFL),

5. Wearables in neurological conditions

Impaired gait and poor postural balance emerge with the development of a neurological condition and both are challenging to recover despite rehabilitation programs [223]. Therefore, accurate identification of these neurological conditions and understanding the underlying pathology may contribute to better and more targeted treatment. Those at risk may display a minimal number of abnormal gait and postural balance deficits from the early stages of a disease. Individual signs are never pathognomonic for any specific disorder but rather come with an associated differential diagnosis [224]. However, some neurological gait studies report some unique gait deficits, linked to different regions of the brain which are susceptible to various conditions. Here, we present reported characteristics of gait together with technologies and techniques used for instrumentation in groups stratified by generic neurological condition. Investigation of temporal and spatial measures using wearable devices in gait assessment of different pathologies are presented in Table 3.

5.1. Stroke

About half of post-stroke sufferers clearly present motor impairments such as synkinesis, abnormal muscle tone, and orthopaedic deformations [15]. More than half of stroke victims walk with hemiplegic gait, which is characterized by the change in the temporal and spatial outcomes, e.g. decreased stance phase and prolonged swing phase of the paretic side [53]. In addition, a significant decrease in the stride time and cadence are most likely to be observed in post stroke groups [125, 225]. A foot mounted IMU (±8g, 100Hz) was used to obtain gait characteristics, where increased stride time and decreased stride length and velocity were reported [125]. Elsewhere [187], as a result of an investigation of the muscle activity for both stroke and healthy subjects, the number of burst in tibialis anterior (TA) during swing phase was found significantly lower in asymmetric stroke patients. Descriptive EMG measure and altered muscle activation patterns (AMAP), were compared for post-stroke hemiparetic gait and healthy controls to identify the alterations in the EMG gait patterns of stroke population. Results indicated that significant numbers of stroke survivors experienced altered muscle activation patterns in some muscle groups (soleus, tibialis anterior, and medial gastrocnemius) in terms of amplitude and onset timing [189].

5.2. Traumatic Brain Injury (TBI)

Gait disorders following TBI (resulting from e.g. blow to the head) are often severe and complex, varying considerably between people [226]. Some TBI sufferers experience severe gait disruption and poor postural balance while others experience relatively mild difficulties. Gait quality of patients with severe TBI was investigated using five IMUs (128Hz) and found a reduced stride frequency, along with an increased stride duration for TBI groups [165]. Free living mobility of mild TBI patients has been investigated with a single IMU (128 Hz, waist) and descriptors of ambulation (e.g. number of bout per hour, total steps per day) as well as turning parameters (e.g. a number of turns, velocity) were studied. Results have suggested that people with chronic mild TBI made larger turns, had longer turning durations together with slower average and peak velocities [162]. Abnormal muscle activation patterns have also been investigated with chronic gait deficits after TBI, where participants who experienced TBI exhibited characteristics changes in the temporal coordination of select lower extremity muscles, which may have an impact on impaired walking during challenging tasks (e.g. dual tasking) [191].

5.3. Hypoxic-Ischemic brain injury (HIBI)

HIBI mostly occurs as a result of cardiac arrest or respiratory failure and deprivation of adequate oxygen supply, which may result in death or long term impaired gait [227]. As in many neurological conditions, HIBI patients often show different movement disorders like chorea and dystonia with reduced walking speed and cadence [228]. Although, individuals after HIBI rarely experience freezing of gait (FOG), 3D motion analysis and force plate based study results showed that HIBI sufferers with FOG have reduced velocity, stride length and increased double support time comparing to those without FOG episodes in HIBI group [229]. To the authors' knowledge, no gait assessment studies have investigated gait characteristics of HIBI using wearables (see supplementary material 3).

5.4 Parkinson's Disease (PD)

A neurodegenerative disease with resting tremor, bradykinesia and rigidity manifestations is one of the most common neurological conditions [230] and with significant developments in the use of wearables to assess PD gait. Reduced walking speed, shortened stride length and increased stride variability are quantified from early stages [12]. Although swing and stance times are sensitive to age and severity of the disease, both are found lower in PD compared to controls [121]. Another

manifestation observed in PD is freezing of gait (FOG), frequently causes falls [231]. Free-living PD gait has been examined with use of a single wearable (lower back) for extended periods (e.g. 7-days) to examine ambulation (e.g. volume, pattern, variability) as well as temporal and spatial gait where the latter were shown to be different to controlled lab conditions [232-234]. Elsewhere, an algorithm that sensitively and automatically distinguishes PD patients from healthy controls was developed using extracted EMG features and support vector machine (SVM) classification [180]. It is reported in an EMG based gait assessment study that PD groups exhibit decreased neuromuscular complexity during gait and muscle activation profiles were also undergo changes compared to controls [181].

5.5. Progressive supranuclear palsy (PSP)

PSP is characterized by poor balance, frontal dysfunction and rapid disease progression. Even though it is challenging to discriminate from PD groups in its early stages, diagnosis may be possible with the study of distinctive spatiotemporal gait parameters. In addition, FOG was reported as an indicator in the early stages, and its presence might improve the clinical diagnosis of PSP condition [235]. A single IMU (250 Hz, lower back) based study reported that PSP survivors experienced lower vertical displacement and higher acceleration than those with PD group in the same cadence. [138]. A walkway based gait study findings suggested that, despite similar disease durations, increased step width and double support found slightly higher in PSP groups than PD groups and always higher than healthy controls [19]. Although some studies investigated spatiotemporal gait characteristics of those with PDP, studies related to muscle characteristics of PDP gait are very limited.

5.6. Cervical dystonia (CD)

CD is a neurological movement disorder in the neck muscles. The condition is associated with involuntary muscle contractions that result in an impaired posture with twisting movements [236]. People with phasic CD experience poor postural control and impaired mobility, especially during walking and turning [237]. Contrary to the majority of neurological conditions, those with CD have increased step length compared to controls as well as displaying increased step time and double support time as reported in a walkway based gait assessment study [238]. To the authors' knowledge, no gait assessment studies have investigated gait characteristics of CD patients using wearables (supplementary material 3).

5.7. Huntington's disease (HD)

An autosomal dominant inherited condition, HD has a different set of movement disorder like chorea, dystonia and bradykinesia. Gait disturbance, unpredictable accelerations and decelerations in gait speed, can be seen from the early stage [239]. In an IMU (250 Hz, upper sternum) based study, spatial gait characteristics and postural balance were investigated for healthy controls, pre manifest HD and manifest HD groups. Results showed a considerable decrease in speed, step-stride lengths together with increased step time asymmetry in the pathologic groups. [167]. Furthermore, changes in motor activity during walking with dual tasking conditions were investigated using EMG and electroencephalogram (EEG). The study findings reported that those with HD, associations with cognitive tests produced only a slight and not relevant deterioration of motor speed and muscle recruitment, whereas some modulation of EEG beta band activity was observed during dual tasking [196].

5.8. Dementia: Alzheimer's disease (AD)

Dementia disease subtypes have been investigated with a single accelerometer (±8g, 100 Hz, lower back) [240]. AD is the most common subtype and damages the stability and symmetry of people's gait explicitly. Reduced stride length and cadence are preliminary deficits observed from the beginning of AD [76, 241]. Increased stride time, stance time and swing time and double support time measures are more likely to be seen in AD groups [145, 242]. IMUs (±4g, 100 Hz, feet and waist) were used to detect gait abnormalities and postural balance of those with AD group and controls during single and dual tasking. Findings showed that those with AD have slower gait speed and lower stride length, whereas balance task findings reported that those with AD experienced a significantly larger average sway speed in Medio-lateral (ML) direction compared to controls [145]. There have been increasing reports of non-cognitive symptoms (e.g. loss of motor function) associated with AD; thus a review investigated links between motor function and preclinical AD [243]. Findings suggested that the change in BMI, lower levels of function (muscle strength) together with both a lower level and more rapid rate of motor decline may be an early cognitive sign of AD.

5.9. Multiple Sclerosis (MS)

MS is commonly known for ataxia and weakness impairments [17]. Significant reductions have been reported in step length and velocity with use of single IMU [150]. Alternatively, two wireless IMUs (102.4 Hz, each shank) compared early MS patients to controls during a Timed-Up-and-Go (TUG) test. Classification with 53 extracted mobility parameters showed that those with early-stage MS could be distinguished with 96.90% accuracy [244]. Free-living physical activity of patients with MS was monitored with wearables (approx.20 days), reporting that the least disabled MS patients performed significantly higher step numbers than those with severe MS [245]. Ankle mobility was investigated for MS patients using EMG sensors (with motion analysis system) and study findings suggested that a decline in ankle push-off may be the common factor to induce limited walking ability in MS groups [192]. In [17], muscle activities in plantarflexion muscle groups were investigated for those with MS patients and controls, where results suggested that plantarflexion muscle groups in those with MS demonstrated an increased EMG amplitude.

5.10. Cerebellar Ataxias (CA)

Cerebellar Ataxias (CA) are a series of gait disorder as a result of impaired cerebellum and associated mechanisms, and gait disturbance was found to be one of the most pronounced and disabling symptom for the disease [246]. An IMU (±10g, 20 Hz, lower back) showed decreased gait velocity, cadence and step length [156, 157]. Another study investigated the time-varying multi-muscle co-activation function (TMCf) in the lower limbs and concluded that global co-activation was significantly increased in patients with CA compared to controls [194]. In a similar EMG based study, significantly higher mean co-activity index values were found in specific muscle groups (VL-BF-TA-GAM, Figure 2) during almost all gait phases in the CA groups compared to healthy controls [195].

Table 3. Wearables in neurological gait assessment with increased (↑) or decreased (↓) spatiotemporal outcomes for that groups

Neurological Condition	Ref.	Device - g-*fs*	Algorithms used (section 4.1)	Group	# subject - (Age)	VEL	CAD	SPL	SDL	SPT	SDT	Additional findings
CA	[157]	ACC ± 10 20 Hz	-	HS	56-(57.2)	↑	↑	↑	-	-	-	-
				CA	51-(60.3)	↓	↓	↓	-	-	-	
	[156]	ACC ± 10 20 Hz	-	HS	57-(56.7)	↑	↑	↑	-	-	-	Decreased step regularity is observed in CA patients.
				CA	61-(61.1)	↓	↓	↓	-	-	-	
PD	[28]	IMU ± 6 51.2 Hz	Gait cycle algorithm-14 Spatial algorithm -1	HS	101-(41-84)	↑	↑	↑	↑	-	↓	Increased stance phase and reduced swing phase are found in PD.
				PD	190-(36-85)	↓	↓	↓	↓	-	↑	
	[125]	IMU ± 8 100 Hz	Gait cycle algorithm-15	HS	15-(68.47)	↑	↑	-	↑	-	X	Reduced swing time, non-significant difference for stance time in both group
				PD	5-(76.20)	↓	↓	-	↓	-	X	
	[121]	ACC ± 8 50-100 Hz	Gait cycle algorithm-1 Spatial algorithm -3	HS	30-(66.6)	↑	-	↑	-	↓	-	Reduced stance and swing time, increased stance and swing time asymmetry in PD group.
				PD	30-(66.9)	↓	-	↓	-	↑	-	
	[139]	ACC ± 10 100 Hz	Gait cycle algorithm-17	HS	-	↑	-	-	↑	↓	↓	Decreased step frequency, single support time and increased double support time in PD group.
				PD	-	↓	-	-	↓	↑	↑	
	[138]	ACC N/A 100 Hz	-	HS	24-(73.7)	↑	↑	↑	-	↓	-	Increased double support and step time variability in PD group.
				PD	124-(68.4)	↓	↓	↓	-	↑	-	
	[205]	MIMU ± 6 128 Hz	Gait cycle algorithm-8 Spatial algorithm -2	HS	10-(69.7)	↑	-	-	↑	↓	↓	Increased stance time in PD group
				PD	10-(73.8)	↓	-	-	↓	↑	↑	
HD	[167]	ACC ± 2.5-10 250 Hz	Gait cycle algorithm-2 Spatial algorithm -3	HS	10-(56.45)	↑	↑	↑	↑	↓	-	Increased step time asymmetry observed in manifest HD group.
				HD	14-(51.83)	↓	↓	↓	↓	↑	-	
	[205]	MIMU ± 6	Gait cycle algorithm-8 Spatial algorithm -2	HS	10-(69.7)	↑	-	-	↑	↓	↓	Increased stance and swing time in HD group
				HD	10-(50.3)	↓	-	-	↓	↑	↑	

Neurological Condition	Ref.	Device - g-*fs*	Algorithms used (section 4.1)	Group	# subject - (Age)	VEL	CAD	SPL	SDL	SPT	SDT	Additional findings
		128 Hz										
PSP	[138]	ACC N/A 100 Hz	-	HS	24-(73.7)	↑	↑	↑	-	↓	-	No significant difference in double support. Increased step time variability in PSP.
				PSP	20-(71.8)	↓	↓	↓	-	↑	-	
Stroke	[125]	IMU ± 8 100 Hz	Gait cycle algorithm-15	HS	15-(68.47)	↑	↑	-	↑	-	↓	Increased stance and swing time in stroke group
				Stroke	4-(51.50)	↓	↓	-	↓	-	↑	
	[205]	MIMU ± 6 128 Hz	Gait cycle algorithm-8 Spatial algorithm -2	HS	10-(69.7)	↑	-	-	↑	↓	↓	Increased stance and swing time in stroke group
				Stroke	10-(58.6)	↓	-	-	↓	↑	↑	
Stroke-Paretic-non paretic	[126]	IMU 100 Hz	-	Non paretic	25-(66.6)	↓	↓		↓		↑	Reduced double support phase in paretic side.
				Paretic		↑	↑		↑		↓	
AD	[145]	IMU ± 4 100 Hz	Gait cycle algorithm-16	HS	50-(59.86)	↑	↑	-	↑	↓	↓	Increased stance and swing time in AD.
				AD	21-(61.48)	↓	↓	-	↓	↑	↑	
	[146]	IMU ± 2 100 Hz	Gait cycle algorithm-18	HS	3-(69.0)	↑	↑	-	↑	↓	-	Reduced mean stride frequency and increased stance phase in AD.
				AD	9-(71.0)	↓	↓	-	↓	↑	-	
MS	[149]	IMU 50 Hz	Gait cycle algorithm-12	HS	15-(57.9)	-	↑	-	-	↓	↓	-
				MS	45-(58.2)	-	↓	-	-	↑	↑	
	[150]	IMU N/A	-	HS	47-(39.4)	↑	↑	-	↑	↓	-	Minor differences for stance and swing phases (% of the GC), and increased double support time was reported for MS group.
				MS	105-(42.2)	↓	↓	-	↓	↑	-	

HS: Healthy subject, X: the same value, (-): not available, g=force, Fs= sampling frequency, VEL: velocity, CAD: cadence, SPL: step length SDL: stride length, SPT: step time, SDT: stride time

6. Discussion

To date, a large number of signal-based parameters have been quantified using various technologies and used along with different gait models to better understand impaired gait due to one or more neurological condition [69, 70, 72]. Existing gait models may be limited as some originated from non-wearable technology-based temporal and spatial outcomes, later adapted for wearable purposes. Current models also fail to include kinematic, kinetic or muscle activation characteristics, which could prove beneficial. Furthermore, proposed models are developed for a particular neurological condition, meaning they may not translate to other pathological cohorts. Thus, developing a model based on more gait characteristics for use in specific pathologies may contribute to better understanding and assessment of impaired gait.

Wearable IMU-based temporal and spatial outcomes are presented extensively in the literature but novel frequency and time-frequency outcomes are becoming more evident and may provide further insights to free-living gait assessment. Alternatively, use of EMG for muscle characteristics of impaired gait have been studied for some neurological conditions (e.g. PD, MS) and distinctive muscle related parameters have been reported [17, 191, 247, 248]. However, the number of gait studies, which investigate muscle activities in other pathologies are limited. Moreover, it was found that there is a large variance in the methodology of sEMG use such as placement protocols. Although there are guidelines for use of sEMG [171, 172], there are few studies adhering to these recommendations.

Under favour of wearable sensing technologies, gait assessments of pathologies have been moving away from clinics to free-living environments. Free-living gait assessment contributes to the existing knowledge because it reflects real-life settings such as environmental factors and natural dual-tasking. Although the majority of gait abnormalities have been studied in the clinical environment, very few neurological conditions and very small populations were studied during free-living. Instrumented gait is predominately investigated in PD and trends to monitor during free-living show large discrepancies for temporal and spatial outcomes between lab and free-living assessment [232-234]. However, the number of evidential studies to investigate whether there are large variances between lab and free-living assessment for other neurological conditions (e.g. Stroke, MS, AD) is very limited. Next, we discuss potential limitations, and future directions in wearable-based gait assessments, including inertial algorithms, multiple sensor fusion and free-living gait assessment.

6.1 Wearable signal processing – future directions

Use of wearable, primarily IMUs, have been validated and used in gait assessment of various neurological conditions (e.g. PD [121, 141], stroke [126, 135], AD [145, 146], MS [154, 249], CA [158, 159], HD [167, 168]). A plethora of inertial gait algorithms were used in these studies (section 4.1). The abundance of inertial algorithms is possibly due to the redundancy of preferred experimental protocols in methodology (e.g. statistical, mathematical) and data capture (e.g. sensor placement). However, both lack of standardisation and the fact that these inertial-based algorithms were developed for a particular pathology are some limitations in the field. Although a comparative assessment study was performed for 5 different inertial algorithms to estimate gait temporal parameters using a single IMU (on L5) within three different pathologic groups (stroke, PD and HD) [250], the most appropriate algorithm for each pathology or for pathologies that experience similar deficits is still unclear. Due to these inconsistencies, developing conclusive interpretations of existing evidence based on wearables remains limited. Perhaps, a manual similar to sEMG guides can be developed for IMUs data capture and methodology to standardise use of wearable sensors in gait assessment of different pathologies. Furthermore, wearable validation studies should adopt the V3 approach of clearly presenting verification (bench testing), analytical validation (efficiency and accuracy of sample-level sensor measurements into physiological metrics) and clinical validation (acceptably identifying or measuring clinically meaningful outcomes in a stated context of use with a predefined disease/condition) approaches within standalone or within a series of research output/papers.

6.1.1 Data synchronisation & fusion

Multiple sensors are used commonly in gait assessment of neurological conditions. Depending on the application (e.g. joint kinematics, muscle characteristics) a number of IMUs, pressure, EMG sensors and clinical based technologies have been used collectively [41, 251]. Although, there are some studies that use multiple IMUs for kinetic gait analysis [115, 252] and lab based systems along with EMG [184, 187, 191, 247] for muscle activation analysis, the number of studies that use multiple wearable sensors e.g. IMU and EMG is very limited. It is believed that this limitation is because of the incapability of technical devices. Previously, commercially available devices were not capable of capturing multiple gait characteristics (e.g. spatiotemporal and muscle activation) simultaneously, while multiple device configurations bring complexities such as data synchronisation and sensor data fusion.

Synchronization of sampling frequencies (i.e. interpolation) has utmost importance to achieve an accurate assessment. Using multiple devices with different sampling frequencies result with data loss or drift error and may not

reflect simultaneous information. Utilising time stamps on devices to be synced provides convenience without the need of additional ports. With the recent advancements in wearables, commercially available sensors (e.g. *BioStamp RC, Shimmer3 EMG, Trigno Avanti* and *Ultium EMG*) can provide inertial sensing and muscle activation signals simultaneously in a single device. It is believed that this convenience will open up new studies to overcome the limitations of previous gait studies e.g. gait models based on spatiotemporal parameters/outcomes only. The second complexity of use of multiple sensors (sources) is sensor data fusion (also known as multi sensor data fusion), which is a process of integrating multiple data sources to produce more consistent and reliable output. The type of data fusion algorithm depends on the target application considering required output, operational time and battery life. To date, data fusion algorithms have been used in activity recognition [253, 254], fall detection[255, 256], gait analysis [257, 258]and biomechanical modelling [259, 260]. Further discussion on data fusion algorithms; signal level, feature level and decision level can be found in [261].

6.1.2. Data Reduction; activity and terrain detection

Although wearable technology makes it possible to collect data for an extended time in free-living conditions, convincing data collection period has not yet been established [232]. In this sense, a greater number of gait assessment studies using wearables in free-living is required to establish satisfactory data collection periods for each pathology. Alternatively, continuous data recording, especially with high sampling frequencies may result in a vast amount of data that includes different daily dynamic gait activities (e.g. level walking, stair ascend) and static activities (e.g. sitting, lying). Therefore, it is essential to process the collected data to extract meaningful gait information for a more comprehensive assessment. Currently, activity recognition with IMUs has been a widely used approach to segment dynamic movements from static. However, there is a large discrepancy observed for the preferred sensor numbers and locations. Considering the comfort and long hours recording possibilities, a single sensor on the wrist [262], two inertial sensors attached to feet [258], a single accelerometer on the chest [263] and a single accelerometer in the level of the waist [264] seem preferred during free-living activity detection. However, considering neurological conditions, the attachment of a single sensor to waist may be ideal for both activity recognition and extraction of gait measures (e.g. cadence, stride length).

Similar discrepancy is observed in preferred methodologies. Physical activities have been classified using IMUs with traditional (e.g. threshold based) [265], time-frequency (e.g. DWT) [263] and analytical (e.g. statistical schemes) [264] approaches. Although, threshold-based and time-frequency algorithms provide high accuracy data classification, the need for calibration limits these approaches. Moreover, pre-determined threshold rates may not translate between different neurological conditions. Conversely, supervised methods that include machine learning (ML) and artificial intelligence (AI) based neural networks (NN) have been preferred due to many advantages like less sensitive to sensor location, high accuracy results and ability to be trained. In previous studies, activity recognition with modern ML and AI approaches typically consists of two different stages; (1) feature selection and (2) classification. In the former stage, appropriate time domain (e.g. mean, signal magnitude area, skewness, variation) and frequency domain (e.g. energy, entropy) features are extracted [262]. In the latter stage, extracted features are used in training and testing to cluster different physical activities. Supervised classification techniques; k-Nearest Neighbour (k-NN), support vector machines (SVM), Random Forest (RF) and unsupervised; k-Means, Gaussian mixture model (GMM) and Hidden Markov Model (HMM) are commonly used ML techniques [253, 254]. However, discrepancy for appropriate selected features and classification techniques and the scarcity of labelled data are impeding factors. Therefore, a deep long short-term memory (LSTM) neural network architecture together with the spectrogram based feature extraction approach are alternatives used for activity recognition with inertial data [266, 267]. ML and AI approaches may be extremely useful for better analysing free-living wearable data.

Better understanding free-living gait may become more meaningful when we know on which surface (e.g. terrain) it is performed. It is reported that gait adaptations strategies to maintain stability are sensitive to different walking surfaces [268]. Older adults are known to be less sensitive to maintain balance in the moment of trips and slips when walking on different terrains due to deterioration in their sensory, motor and cortical functions [269]. In previous studies, indoor-outdoor and hard-soft walking terrains (e.g. tiles, carpet, grass) were accurately classified using SVM and RF with acquired inertial data from the chest and lower back [270], and indoor walking terrains were investigated with an IMU attached to lower back [271]. Although only a few studies investigated gait on the uneven terrain for neurological conditions using clinic based technologies [272], wearable based gait assessment for those populations on different terrains have not been fully investigated. Thus, it is believed that extracting specific periods of gait together with the walking terrain may be useful to better understand how neurological conditions adapt to walk on different terrains (multi-surface). Then, this insightful knowledge may contribute to the design of interventions (e.g. bespoke rehabilitation program) for people with neurological conditions to improve impaired gait, poor postural balance and minimise falls.

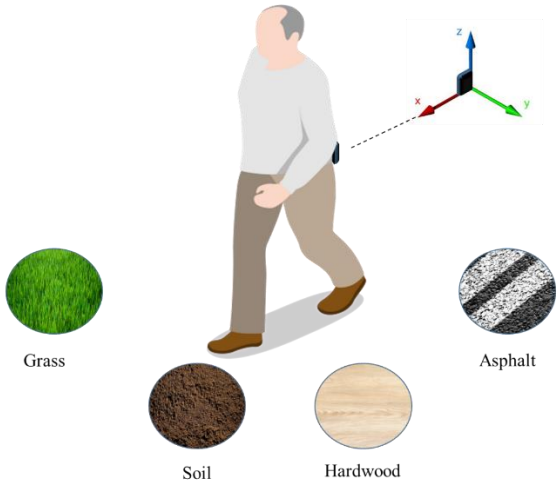

Figure 4. Walking on different terrains

7. Conclusion

This scoping narrative review examined the approaches and fundamentals of instrumented gait assessment by examining the conceptual models, which have been created for pragmatic interpretation. We found that some were created from non-wearable technology, later adapted for use with IMU-based wearables. Current models may be limited due to their reliance on IMU-based outcomes only but with developments in (commercial-based) wearables, there are new opportunities for more in-depth, free-living gait studies on a range of neurological cohorts where many have yet to be robustly studied. This is particularly applicable to the use of multi-sensor type wearables (i.e. sensor fusion) for use beyond the lab, where more insightful and habitual gait data can be captured on the individual. This creates opportunities in the field as newer gait models need developing as well as the creation of multi-sensor algorithms to quantify kinetic and kinematic gait characteristics. However, the field will continue to be fragmented and face ongoing challenges given the adaptability of wearables and the lack of standardised approaches to quantify gait (e.g. sensor placement), including sporadic use of algorithm methodologies (mathematical formulae). Processes to be considered to move the field together and forward is the adoption of suitable guidelines that must and should be adhered to. This includes acknowledgement and implementation of the process pertaining to robust validation (e.g. V3) as well as pragmatic guidelines for correct use of wearables during clinical testing (e.g. SENIAM). Process and guidelines such as those will aid the next wave of targeted gait assessment in the home and community where so many environmental unknowns will complicate interpretation of gait outcomes from high resolution, multi-model sensing.

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Supplementary material 1.

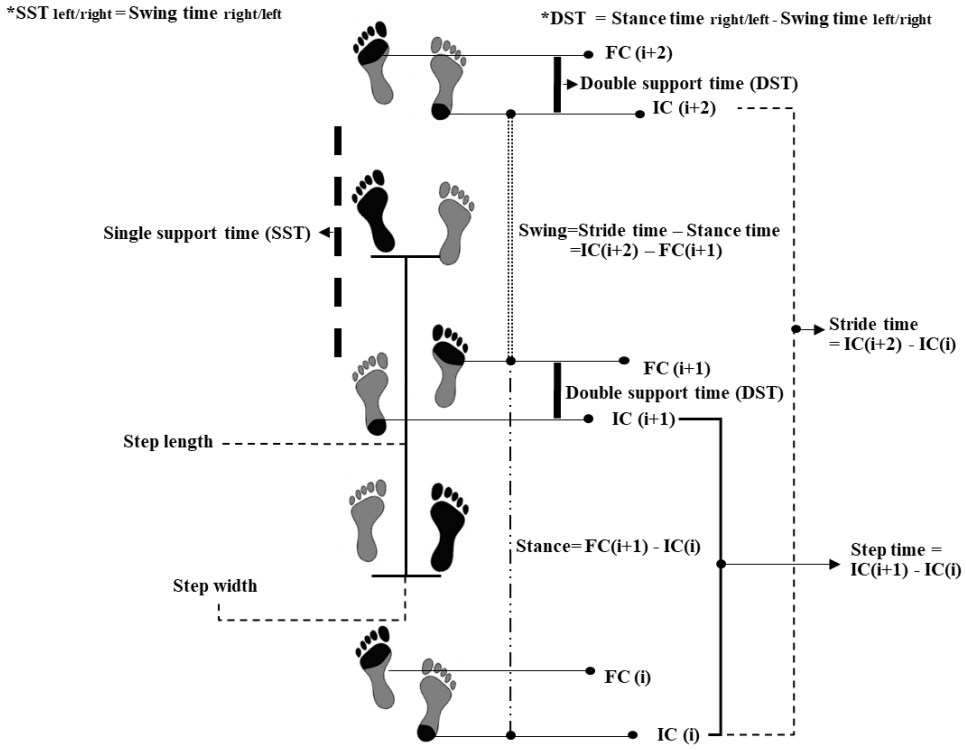

Figure S1. Temporal timings and formulae [49, 273]

Supplementary material 2.

Spatial measure formulae:

1.(Foot based) One way of calculating stride length is the computation of double integration of gravity correlated accelerometer signal. This approach is not widely preferred as it includes various of complex subsections like orientation estimation, gravity removal and de-drifting [210].

2.(Shank based) Trojaniello et al. proposed a more extensive method to estimate stride length using two consecutive initial contacts (ICs) of the same foot. The proposed method removes the gravity then uses Optimally Filtered Direct and Reverse Integration along with high pass filter to reduce the effect of drift in the accelerometer signal. In the final stages, AP acceleration is integrated to obtain AP velocity and AP displacement with a further integration [205].

3. (Lower trunk based) Another approach to estimating the step length is the use of inverted pendulum model; $\text{step length}=2\sqrt{2lh-h^2}$,where h is the change in the height of CoM, and l is the sensor height from the ground, detailed [200].

4. (N/A) Weinberg proposed an alternative way to calculate the step length as a function of the difference between max and min vertical acceleration during steps: $\text{step length}=K\sqrt[4]{A_z,\text{max}-A_z,\text{min}}$, where K is a regression coefficient and Az represents the acceleration in vertical axis [274].

5. (Upper trunk based) In another approach, step length is calculated as a function of variance of the vertical acceleration $\text{step length}=c+d\sqrt{\text{Var}(Az)}$ where c, d and Az are regression coefficients and vertical acceleration, respectively [275].

6. (Lower trunk and lower limb based) Step width is lateral distance between two feet. Pythagorean theorem can be used to estimate step with $SW=2*Step\,length*\tan(\theta)$, where θ is rotational yaw angle of the IMU placed at leg in which step was executed [276].

Supplementary material 3.

To the best of the author's knowledge, no studies have investigated the temporal and spatial measures using wearable sensors for those with Hypoxic-Ischemic brain injury or Cervical dystonia. Therefore, to provide a guide for the reader in terms of all pathologies mentioned in the section 5, Table S1 presents studies that used non-wearable technologies to investigate the spatiotemporal outcomes.

Table S1. Clinic based devices in neurological gait assessment with spatiotemporal outcomes

Neurological Condition	Ref.	Device	Group	# subject - (Age)	Findings							
					VEL	CAD	SPL	SDL	SW	SPT	SDT	Additional findings
TBI	[226]	Motion Analysis Vicon 512-Force plate AMTI	HS	25-(27.8)	↑	↑	↑	-	-	-	-	Increased stance duration, double support and base of support in TBI
			TBI	41-(29.1)	↓	↓	↓	-	-	-	-	
HIBI FOG	[228]	Motion Analysis VICON MX-T10 Motion Analysis System, Oxford Metrics Inc., Oxford, UK	HS	15-(40.27)	↑	↑	↑	↑	-	↓	↑	Increased stance time and double support, decreased swing time and single support. Higher asymmetry in step length and time in HIBI with FOG.
			HIBI FOG	13-(37.36)	↓	↓	↓	↓	-	↑	↓	
HIBI with and without FOG	[229]	Motion Analysis VICON MX-T10 Motion Analysis System, Oxford Metrics Inc., Oxford, UK	HIBI	17-(48.88)	↑	↓	↑	↑	-	↓	↑	Increased stance time and double support, decreased swing time and single support in HIBI with FOG.
			HIBI-FOG	12-(37.83)	↓	↑	↓	↓	-	↑	↓	
CD	[238]	Walkway CIR Systems, Inc. GAITRite System	HS	10-(52.8)	↑	-	↓	-	-	↓	-	When corrected for walking speed, people with CD demonstrated higher step time variability and lower step length variability.
			CD	10-(53.9)	↓	-	↑	-	-	↑	-	

HS: Healthy subject, X: the same value, (-): not available, g=force, Fs= sampling frequency, VEL: velocity, CAD: cadence, SPL: step length SDL: stride length, SW= step with, SPT: step time, SDT: stride time