Human Gait Analysis in Neurodegenerative Diseases: a Review

Grazia Cicirelli, Donato Impedovo, *Senior, IEEE*, Vincenzo Dentamaro, *Member, IEEE*, Roberto Marani, Giuseppe Pirlo, *Senior, IEEE* and Tiziana R. D'Orazio

***Abstract*—This paper reviews the recent literature on technologies and methodologies for quantitative human gait analysis in the context of neurodegnerative diseases. The use of technological instruments can be of great support in both clinical diagnosis and severity assessment of these pathologies. In this paper, sensors, features and processing methodologies have been reviewed in order to provide a highly consistent work that explores the issues related to gait analysis. First, the phases of the human gait cycle are briefly explained, along with some non-normal gait patterns (*gait abnormalities*) typical of some neurodegenerative diseases. The work continues with a survey on the publicly available datasets principally used for comparing results. Then the paper reports the most common processing techniques for both feature selection and extraction and for classification and clustering. Finally, a conclusive discussion on current open problems and future directions is outlined.**

***Index Terms*—Human gait analysis, Sensors, Features, Classification Methodologies, Neurodegenerative Diseases.**

I. Introduction

In the last decades, the number of patients with neurodegenerative diseases (NDDs) has been growing rapidly, given the remarkable improvements in life expectancy. Currently, neurodegenerative diseases, such as Alzheimer's Disease (AD), Multiple Sclerosis (MS), Parkinson's disease (PD), Huntington's disease (HD), dementia, etc., are not curable. The World Health Organization (WHO) predicted that within 2030, neurological disorders will represent the second leading cause of death, worldwide [1]. Currently available treatments can only limit the rapid progression of the disease.

Neurodegenerative diseases share symptoms that involve progressive cognitive decline, limiting everyday functional abilities and leading to motor dysfunctions, including deficits in gait and balance [2], [3]. The link between cognitive impairment and altered mobility performance has been widely studied and recognized [4], [5]. The continuous and regular monitoring of the mobility performance of elderly people may help diagnosis and assessment of the severity of neurological disorders. Mobility tests are usually administrated by physicians or specialized physiotherapists in order to measure patients' functional mobility and still rely on observation-based assessment [6]. In the last years, technological and methodological advances have opened up the potential to provide objective measures of mobility performance in order to aid understanding neurological conditions in an automatic fashion [7].

Quantitative measurements of mobility performance have major advantages from different perspectives: social, clinical and patient-centered. It can provide clinicians with pivotal information on health status and cognition informing about the disease severity and progression; help to distinguish cognitive impairments; help to timely intervene for maintenance and promotion of self-independence of patients; help to capture mobility variations during time (both improvements or degenerations); improve patients' quality of life; be of support to evaluate fall risk and so to prevent falls; reduce the heavy burden of relatives and caregivers; reduce socio-economic costs [7], [8], [9].

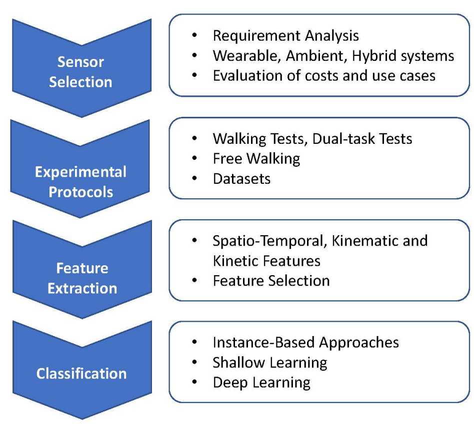

Fig. 1. Main steps of instrumented gait analysis.

Several fine reviews on instrumented gait performance evaluation have been published in the last years, demonstrating considerable interest in this area [2], [3], [7], [10], [11], [12], [13]. Many published reviews list plenty of works that show the strict relationship between mobility deficits and cognitive impairment for different purposes: differentiating

This work was supported in part by Apulian Region (Regione Puglia POR FESR—FSE 2014–2020. Fondo Europeo Sviluppo Regionale. Azione 1.6—Avviso pubblico "InnoNetwork") under Grant "BESIDE" Nr. YJTGRA7.

Grazia Cicirelli, Roberto Marani and Tiziana R. D'Orazio are with the Institute of Intelligent Industrial Systems and Technologies for Advanced Manufacturing (STIIMA), of the National Research Council of Italy (CNR), 70126 Bari, Italy. Donato Impedovo, Vincenzo Dentamaro and Giuseppe Pirlo are with Computer Science Department, University of Bari, 70126 Bari, Italy
(*Corresponding Author: grazia.cicirelli@stiima.cnr.it*).

Manuscript received month day, year; revised month day, year.

Mild Cognitive Impairment (MCI) patients from cognitively intact older adults [2], identifying MCI subtypes [3], [12], [14] studying disease progression in PD, ataxia and dementia [7], demonstrating the relationship between gait, emotions and mood disorders [10], and so on. The previously mentioned reviews are mostly related to medical and motor aspects of diseases and do not contain specific aspects connected to the methodologies that can be applied. Other reviews focus only on technologies either investigating their usability and acceptability by older adults with MCI and dementia [15] or exploring ambient sensors for elderly care and independent living [16] or exploring wearable sensors [11]. Few works exist which explore the methodological approaches to gait analysis by both computer vision and pattern recognition points of view [17], [18]. However these last works address big data issues related to gait [17] or methodologies for recognizing an individual (i.e. biometric recognition) by his/her gait [18].

Differently from previous reviews, this article provides a self-consistent overview of all the aspects related to the instrumented evaluation of gait parameters in neurodegenerative diseases (see Figure 1). The article describes how the biometric technologies and methodologies (data sensing, signal processing, feature engineering, pattern recognition and Computer Vision) can be used for the specific aim of neurodegenerative diseases evaluation. To this aim, referenced papers have been selected by searching IEEE Xplore, ScienceDirect, Scopus, PubMed and ACM scientific databases considering those published in the last decade. The search terms used to categorize articles were "gait analysis" joined with AND/OR connectives with the key terms "neurodegenerative disease", "Parkinson", "Alzheimer", "Sclerosis", "Huntigton" and "dementia". As this is not a systematic review, a screening method has been applied for selecting studies that better covered the different aspects of applied technologies and methodologies useful for the discussion carried out. As a result, the work has been organized taking into account the pipeline of a typical pattern recognition system. The gait cycle is firstly introduced (section II) along with most frequently abnormal patterns associated with the most common neuromuscular diseases (section III). Gait sensing technologies are reported in section IV organized in terms of ambient sensors, wearable sensors and hybrid approaches. Acquisition protocols and available datasets are reported, respectively, in sections V and VI. Features and classification techniques are described in sections VII and VIII. Section IX summarizes the main findings along with related open issues. Section X concludes the article.

II. The Gait Cycle

Gait Analysis studies the ways both humans and animals walk [20], [21]. A gait cycle is a succession of physical actions performed during walking that involve the motion of lower limbs. Formally, the gait cycle is defined as the interval between two successive heel strikes of the same foot (step). It is also known as stride and consists of two phases: the stance phase and the swing phase which alternate for each leg as shown in Fig. 2. The stance phase includes the heel-to-toe contact sequence of the foot. The swing phase proceeds with the foot suspended in the air. On average stance phase accounts for 60% of the gait cycle, whereas the swing phase for 40%. Furthermore, each phase includes a sequence of Double Support (both feet are in contact with the ground) and Single Support (only one foot is in contact with the ground) sub-phases (see Figure 2). These definitions are valid for all the studies on gait analysis. Many of the methods presented in this article can be applied for gait analysis in several contexts such as rehabilitation, neurological gait disorders, psychiatric gait abnormalities, gait degradation due to aging, and so on. Depending on the particular context, gait characteristics can be different. This article focuses on the researches done in the particular context of neurodegenerative diseases, narrowing the analysis to a subset of diseases as described in the following section.

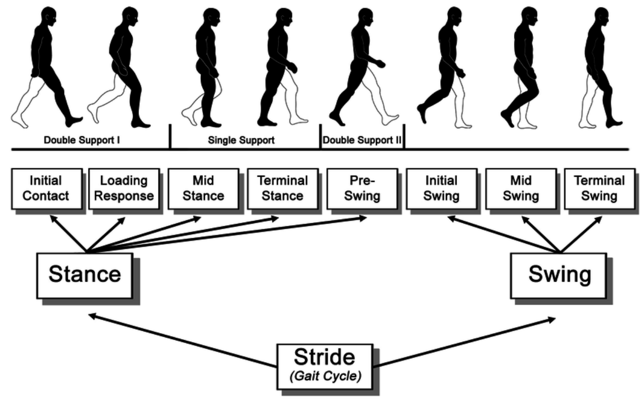

Fig. 2. Gait Cycle phases and sub-phases according to [19].

III. Neurodegenerative Diseases and Gait Abnormalities

Neurodegenerative diseases result in progressive degeneration of neuronal cells. This degeneration worsens over time leading to the death of neurons. As a consequence, neuromuscular control is compromised causing problems with balance and walking (ataxia) or with mental functioning (dementia) [22], [23]. In the last years, a considerable research effort has been devoted to the study of gait analysis in medicine. Despite the wide spectrum of neurodegenerative diseases, the majority of research attention has been focused on gait pathologies related to Alzheimer's disease (AD), Parkinson's Disease (PD), Multiple Sclerosis (MS), Amyotrophic Lateral Sclerosis (ALS), Huntington's Diseases (HD), and various forms of Dementia.

AD is the most common neurological disorder. On the early disease stage, AD patients exhibit difficulties with memory and comprehension. With time other cognitive domains are affected including language and visual-spatial functions. As a consequence gait deteriorates due to the strict association between gait and cognition [12], [14]. AD patients show hyperkinesia, apraxia, and abnormalities in walking and trunk movements. Gait disturbances reported in early AD include slower gait with shorter stride length, lower cadence (longer stride time/gait cycle) and greater stride-to-stride variability [24].

PD is the second most common neurodegenerative disease after AD. PD involves the primary type of hypokinetic movement disorder resulting in slow movements (bradykinesia) of PD patients. The most common symptoms include body rigidity (hypertonia), tremor, flexed posture, loss of postural reflexes and freezing, especially in the severe stage of the disease. Primary gait disorders in PD patients are reduced gait speed and step length, festination, impaired rhythmicity, and increased axial rigidity [25].

MS is a disease that affects the central nervous system, causing progressive disability in young adults and a wide range of potential symptoms, including muscle weakness, physical fatigue, lack of coordination, problems with arm or leg movement and balance. Motor weakness, spasticity, ataxia and sensory disturbance are common neurological deficits even at the early stages of the disease, causing significant impairment of gait [26].

ALS is a disorder primarily affected by the loss of the motoneurons of the cerebral cortex and brainstem. ALS patients exhibit a deterioration of gait during the course of the disease. Decreased walking velocity, stride-to-stride instability and perturbations in the fluctuation dynamics (how the stride time changes from one stride to the next) have been principally observed in ALS patients [27].

HD is a result of a neurodegenerative process that causes uncontrolled movements, emotional problems and loss of cognitive abilities. As the disease progresses, uncoordinated body movements and unsteady gait become more apparent. HD patients show several changes in gait parameters such as slow walking velocity, decreased step and stride length, increased stance phase, and decreased swing phase [28].

In conclusion, it becomes apparent, from extant studies, that gait dysfunction is prevalent in subjects with a cognitive decline with respect to cognitively healthy subjects. So, gait analysis can provide a concrete additional aid for dementia diagnosis and then for distinguishing among different dementia sub-types [3], [29]. In Table I a summary of relationships among gait characteristics and the above-listed diseases is given.

TABLE I
GAIT CHARACTERISTICS IN THE MOST COMMON NEURODEGENERATIVE DISEASES

NDD	Symptoms	Gait Characteristics
Alzheimer's Disease (AD) [24]	Hyperkinesia, apraxia, abnormalities in walking and trunk movements	Decreased walking speed Decreased stride length Increased support time Greater stride-to-stride variability Lower cadence
Parkinson's Disease (PD) [30]	Hypokinetic movement, bradykinesia, hypertonia, tremor, flexed posture, festination, loss of postural reflexes and freezing	Decreased walking speed Increased cadence Reduced stride length Reduced swing time Higher double support time
Multiple Sclerosis (MS) [31]	Motor weakness, spasticity, ataxia and sensory disturbance	Decreased walking speed Shorter step length Reduced cadence Increased double support time
Amyotrophic Lateral Sclerosis (ALS) [27]	Perturbations in the fluctuation dynamics, altered gait rhythm, weakness in legs, feet or ankles	Decreased walking speed Increased stride time variability Increased stride time
Huntington's Diseases (HD) [28]	Uncontrolled movements, emotional problems, psychiatric disorders and loss of thinking abilities	Decreased walking speed Decreased step/stride length Increased stance/swing phase Decreased single support time

IV. SENSORS

Different types of sensors have been used in literature for real-time data acquisition of human gait. They can be classified into two main categories [32]: Wearable Sensors and Ambient Sensors.

Wearable sensors are usually placed on different parts of the patient's body and the captured data are usually transmitted through wireless connections or collected on on-board storage devices. Ambient sensors, instead, are mounted in the environment and do not require to be worn by elderly people. A third category can be also obtained if a combination of both the previous ones is considered. In this case, wearable and ambient sensors are used together forming hybrid systems.

A. Wearable Sensors

The recent technological advances have led to the development of miniaturized wearable sensors that can be easily assembled and integrated into small cases for more comfortable and easy wearability [33]. The main wearable sensors used for gait analysis are wearable inertial sensors [34]. These include accelerometers, gyroscopes and magnetometers. Accelerometers are used for measuring directly the linear acceleration of the body or of the body segments they are attached to. Several types of accelerometers are commercially available. Tri-axial accelerometers are mainly used for body motion measurements as they provide amplitude and direction of acceleration in the three-dimensional space [35], [36], [37], [38], [39]. The directions of the axes, X, Y, Z, of the accelerometer reference system, depend on the sensor placement on the patient's body. This reference system, through an anatomical calibration, can be used to extract respectively Antero-Posterior, Vertical and Medio-Lateral directions of people movement [40].

Gyroscopes measure the angular velocity of body segments around a predefined axis in an internal sensor reference system. As in the case of tri-axial accelerometers, tri-axial gyroscopes are more popular as they measure the speed of rotation around all three axes of the reference frame. Gyroscopes and accelerometers are combined in single Inertial Measurement Units (IMUs) that often are attached at the waist level or at different segments of the lower limbs (thigh, shank, ankle, foot, etc.) in order to reconstruct their attitude [41], [42], [43], [44]. The location and orientation of placing an IMU sensor are important as the output of the sensor depends on the position at which it is placed, its orientation, posture and activity being performed. In [45], investigations on the optimal location and orientation of placing an IMU sensor on the barefoot are carried out. This type of study is important as the sensor placement can affect sensor output and inevitably influences the subsequent phase of feature extraction.

IMU sensors can be further equipped with three-axis magnetometers that measure the earth's magnetic field strength and its direction. Magnetometers are usually included in IMUs as they are used as the heading reference. The combination of accelerometers, gyroscopes, and magnetometers has given rise to Inertial and Magnetic Measurement Systems (s) that have open new perspectives for the measurements of kinematic parameters such as the position, the acceleration and the speed produced by the movement [46], [47], [48]. Sometimes inertial systems are integrated with additional sensors such as force and pressure sensors for building instrumented insoles or instrumented shoes in order to obtain supplementary measures as well as vertical ground reaction forces (VGRFs) [49], [50], [51], [52], [53], [54].

B. Ambient Sensors

Contrarily to the wearable body sensors, non-wearable ones are placed in the environment. Among the most commonly used for gait analysis, there are force sensors, pressure sensors and vision-based sensors. Force and pressure sensors are usually deployed on the floor into platforms, mats, or instrumented walkways and capture data while patients walk across them, so they are usually called *floor sensors*. Force sensors measure Ground Reaction Forces associated with walking and provide information about the Center of Pressure (CoP) of the body. As force sensors can be placed in different orientations inside the platforms, the direction and magnitude of ground reaction forces can be measured in three-dimensional space. So, different kinetic information can be derived, which are necessary for a full understanding of gait dysfunctions [55], [56], [57]. Analogously, instrumented walkways, based on pressure sensors, give information about several temporal and spatial gait measures. Differently from force plates, walkways with embedded pressure sensors, have the ability to segment different pressure regions of the foot, providing important information such as contact and peak pressure around these regions [58], [59], [60], [29].

Electronic walkways are often used in conjunction with a Motion Capture System (MCS) for making a more complete analysis of gait by merging the different information coming from both types of systems. MCSs are also employed for the validation of other sensory systems such as webcams or walkways themselves due to their high level of accuracy [61], [62]. Indeed, MCSs are optoelectronic marker-based systems consisting of a number of cameras and a set of retro-reflective markers that are attached to the body of the monitored subjects. Spatio-temporal parameters of gait are accurately measured as the 3D position of each marker is estimated via time-of-flight triangulation [63], [64], [65], [66].

MCSs can be included in marker-based vision systems as they use cameras and need markers in order to make easier human detection on images. They are principally used in research laboratories or controlled environments where their installation is possible. Marker-less vision-based systems, instead, are characterized by cameras that acquire video information of human gait, and then image processing methodologies are applied in order to extract the relevant parameters useful for gait analysis [67].

Among vision-based systems, the most commonly used for gait analysis are RBG monocular cameras, stereo cameras, thermal cameras and the most recently developed RGB-D cameras such as Microsoft Kinect or Intel RealSense [68]. A panoramic description of three-dimensional camera systems is provided in [69] with a critical discussion about the validity and clinical utility of these devices for assessing physical dysfunctions. Actually, the literature on the use of vision-based systems for the instrumented gait analysis of patients with neurodegenerative diseases counts few works compared to those based on wearable sensors or floor sensors. However, in the last few years, the progress in new and low-cost optical technologies together with the development of new and accurate pattern recognition approaches has led to an increase in vision-based research works [70], [71], [72], [73], [74], [75].

Recently, a novel and gradually emerging technology for human activity recognition, including gait detection and analysis, is wireless technology. The deployment of wireless sensing technologies in many applications related to health care and human daily activity recognition, is gaining attention as it performs detection functions with common commercial Wi-Fi devices in a passive manner without the need for users to wear any devices [76], [77]. Wireless sensing systems base on multi-path propagation (i.e. radiation, reflection, diffraction and scattering) of wireless signals in indoor environments. When signals are reflected by a human walking around, the variations of channel state information are processed to obtain gait information such as walking speed, stride length, stride time, and so on [78].

C. Hybrid Systems

The interest in developing more and more efficient objective measurement systems, for providing specialists with increasingly accurate and reliable information, has led to the integration of the different types of sensors, both wearable and ambient, in order to develop the so-called *hybrid systems*. The concurrent use of heterogeneous information acquired by multiple sensors has demonstrated promising performance in the identification of gait patterns associated with individual disease. Various combinations of multiple sensors have been used in the literature for gait analysis in the context of NDDs.

A pervasive context-aware home-based system for PD patients based on distributed sensing has been proposed in [79] for detecting the freezing of gait. The system consists of a network of Kinect cameras and a smartphone (including a tri-axial accelerometer, a gyroscope and a magnetometer) worn by the patient. These elements work independently, so that freezing detection can be achieved using the wearable sensor even when the patient is not in the field of view of the camera. Furthermore, the fusion of both vision and inertial information can provide the hybrid system with efficiency and robustness.

In [80], an approach for combining data acquired from two different sensor modalities is presented. Data from 5 IMU sensors and an optoelectronic marker-based MCS are used for accurate measurement of gait parameters. Similarly, in [81] two sources of motion data, a 3D inertial sensing system and a 3D optical MCS, are used for gait detection and analysis. As the MCS system and inertial system have their respective sampling rates and reference systems, the problem of data synchronization is also addressed.

A more recent work [82] proposes a novel hybrid model to learn the gait differences between NDDs, between different severity levels of Parkinson's disease and between healthy individuals and patients. Heterogeneous data acquired by multiple sensors are aggregated: VGRFs from force-sensors placed inside the shoes; acceleration data from three accelerometers attached to hips and legs of patients; 3D skeleton-joint positions and 2D gait silhouettes by two Kinect cameras. The integration of multi-modal gait features shows the effectiveness of the proposed model in better-discriminating NDDs and detecting disease severity levels.

The use of hybrid systems can be very beneficial when different gait characteristics need to be captured and jointly exploited in order to produce a more consistent and reliable output. However, fusing multiple resources bring complexities based on the level at which the fusion is performed. If it is performed at the sensor or raw data level, then data synchronization, different sampling and transmission frequencies of devices can result in data loss or drift errors. In addition, data can greatly differ in forms and scales. So, these represent open issues often overlooked, but they need to be addressed for building robust integrated systems.

V. Protocols for gait analysis

Defining a protocol for gait analysis is fundamental for making kinematic and kinetic measurements clinically comprehensible and comparable. A protocol defines the biomechanical model used during data collection that necessarily influences the subsequent phase of data processing and analysis, so affecting the clinical interpretation. Different walking tests exist that are used in clinical contexts to evaluate the functional capacity of patients. These tests differ mainly for the distances walked during test performance: 4, 6 and 10 meters are the most common distances used. Walking speed and walked distance are the principal valid and sensitive measures that are informative enough for their clinimetric properties [83]. However, many other spatio-temporal and dynamic features (see section VII for a detailed description) are valid and informative as well as gait speed and can provide useful details regarding particular gait deficits. Measuring different gait features involves the definition of different protocols as what is acceptable for some characteristics is not valid for others. Some clinimetric measures, in fact, are more reliable over longer durations [84], [85]. Furthermore, in order to infer information relative to specific neural areas and cognitive functions, protocols involving the so-called *brain stress tests* are employed [86]. These are the dual-task tests that are composed of walking while performing an additional motor-cognitive task such as calling a phone number [87], talking or counting [88], or carrying a glass of water [89]. However, a considerable number of works in the related literature do not specify the testing protocol used to assess gait parameters, so it is difficult to compare and assess the results.

Moreover, a final consideration must be done regarding clinical and laboratory settings where walking tests are performed. This regards the so-called *Hawthorne effect* or *observer effect* that denotes behavior variations caused by the presence of observers. Patients, in fact, could perform well because of the awareness of being observed. This has led to the necessity of developing systems for long-term gait monitoring, in particular in free-living or home environments in order to reduce contextual factors and obtain more objective results with respect to short-distance gait analysis [24], [72].

VI. Datasets

The recent literature on gait analysis proves the large interest in the use of public datasets as they allow the scientific community to compare different approaches. Furthermore, in the specific context of studying neurodegenerative diseases, gait datasets can be very useful for further analyses and investigations for both classifying different sub-types of gait disorders or for improving and sharing statistical analyses. Table II summarizes some details of the most used datasets on gait.

The Gait in Neuro-Degenerative Disease Database [27] [90] is a collection of 64 recordings of gait from 15 subjects with PD (age ranging from 44 to 77); 20 with HD (age ranging from 29 to 71); 13 with ALS (age ranging from 36 to 70); and 16 healthy controls (age ranging from 22 to 74). The raw data are obtained using force-sensitive resistors, sensitive to pressure, placed inside the shoes of each individual. Time series data have been derived from these raw signals. The same sensors have been used for recording the data of Gait in Aging and Disease Database [90] which contains the walking stride interval time series. The data have been collected from 15 subjects: 5 healthy young adults (23-29 years old); 5 healthy old adults (71-77 years old), and 5 older adults (60-77 years old) with PD. In the above-listed datasets, subjects walk at their usual pace, whereas different walking protocols have been used as detailed in Table II. The Gait in Parkinson's Disease Database [90] is a collection of VGRFs from eight force sensors placed beneath the feet of 93 patients with PD (with a mean age of 66.3 years and with mild to moderate disease severity) and 73 age- and gender-matched healthy controls. The database includes the VGRF records of these subjects as they walked at their usual, self-selected pace for approximately 2 minutes on level ground. This database also includes demographic information, measures of disease severity and other related measures. Furthermore, subsets of the database include measures recorded under three different conditions: 1) considering the effect of Rhythmic Auditory Stimulation (RAS) [91]; 2) walking while subjects perform a second task [92] and 3) walking on a treadmill [93]. In the first subset 29 patients with PD and 26 healthy controls participated to the data acquisition while walking at a comfortable pace for about $100m$ with and without RAS [91]. In the second one, data from 30 patients with PD and 28 healthy control subjects were acquired under usual walking and different dual-tasking conditions for better understanding the motor control of gait and the relationship between cognitive function and gait [92]. In the third subset, 36 patients with PD and 30 healthy controls were studied under three walking conditions for 2 minutes each: 1) usual, unassisted walking on level ground at each subject's self-selected comfortable speed; 2) walking on

TABLE II
DATASETS USED IN LITERATURE FOR GAIT ANALYSIS OF SUBJECTS SUFFERING FROM A NEURODEGENERATIVE DISEASE.

Dataset Name	Data Acquisition Sensor	Sensor Type	Data Type	Data Acquisition Protocol
Gait in Neuro-Degenerative Disease Database (https://physionet.org/content/gaitndd/1.0.0/) (Hausdorff et al. 2000) [27] (Goldberger et al. 2000) [90]	Ultra-thin force-sensitive resistors placed inside the shoes	Wearable	Left and Right foot signals and time series from 15 subjects with PD, 20 with HD, 13 with ALS, and 16 healthy controls	Subjects walk for 5 minutes at their usual pace
Gait in Aging and Disease Database (https://physionet.org/content/gaitdb/1.0.0/) (Goldberger et al. 2000) [90]	Ultra-thin force-sensitive resistors placed inside the shoes	Wearable	Walking stride interval time series from 5 healthy young adults, 5 healthy old adults, and 5 older adults with PD	Healthy subjects walk in a roughly circular path for 15 minutes, subjects with PD walk for 6 minutes up and down a long hallway
Gait in PD Database (https://physionet.org/content/gaitpdb/1.0.0/ (Goldberger et al. 2000) [90]	Eight force sensors underneath each foot	Wearable	Force data as a function of time from 93 patients with PD and 73 healthy controls	Subjects walk at their usual, self-selected pace on flat ground for 2 minutes
Gait in PD with RAS Database (https://physionet.org/content/gaitpdb/1.0.0/; Filename convention: Ju) (Hausdorff et al. 2007) [91]	Eight force sensors under the feet	Wearable	VGRFs measures from 29 patients with PD and 26 healthy control subjects	All subjects (with PD and healthy) walk $100m$ at a comfortable pace with and without RAS
Dual Tasking in PD Database (https://physionet.org/content/gaitpdb/1.0.0/; Filename convention: Ga) (Yogev et al. 2005) [92]	Eight force sensors under the feet	Wearable	VGRFs measures from 30 patients with PD and 28 healthy control subjects	Subjects walk at their normal pace for 2 minutes under usual walking and different dual-tasking conditions
Gait in PD with Treadmill Database (https://physionet.org/content/gaitpdb/1.0.0/; Filename convention: Si) (Frenkel-Toledo et al. 2005) [93]	Eight force sensors under the feet	Wearable	VGRFs measures from 36 patients with PD and 30 healthy controls	Subjects walk three times for 2 minutes each: (1) walking on level ground (unassisted), (2) walking on level ground while using a walker, and (3) walking on a treadmill.
Sensor-based Gait Analysis Validation Data Database (www.activitynet.org) (Kluge et al. 2017) [94]	Two IMU sensors laterally attached to the shoes	Wearable	Inertial data from 15 subjects: 11 healthy subjects and 4 PD patients	Subjects perform four times a straight $10m$ distance with turning movements in between at different walking speeds
IMU-based Gait Data (Barth et al. 2015) [95]	Two IMU sensors laterally attached to the shoes	Wearable	Acceleration and orientation data from 40 elderly controls, 15 patients with PD and 15 geriatric patients	Subjects perform two protocols: straight $40m$ walking test at a comfortable self-selected speed and 2 minutes free walk
Dataset on gait patterns in degenerative neurological diseases (Serrao et al. 2018) [96]	Optoelectronic motion analysis system	Ambient	Spatio-temporal parameters and joint kinematics from 19 patients with CA, 26 patients with HSP, 32 patients with PD and 65 healthy subjects	Subjects walk barefoot at a comfortable, self-selected speed along a walkway approximately $10m$ in length while looking forward
Dataset for gait analysis (Schülein et al. 2017) [97]	Instrumented walkway system and inertial sensors in the shoes	Ambient Wearable	Spatio-Temporal parameters and heel strike, toe off angles and foot clearance from 126 patients	Subjects perform the gait test with and without gait support from a wheeled walker
Dataset for gait analysis (Caicedo et al. 2020) [98]	3D MCS	Ambient	Spatio-temporal gait parameters from 44 older adult population	Subjects perform ten times a walking path of 120
Biomathics consortium, the “Gait, cOgnitiOn & Decline” (GOOD) initiative (Beauchet et al. 2014) [99]	Instrumented walkway system	Ambient	Spatio-temporal parameters from more than 2700 older adults with different stages of dementia and healthy individuals	Subjects walk at their usual self-selected walking speed in a quiet, well-lit environment on a length ranging from $4.6m$ to $7.9m$
Skeletal Information Database (Romeo et al. 2020) [100]	Three Monocular Cameras	Ambient	Skeletal joints data from 27 healthy people and 20 patients affected by neurodegenerative diseases	Subjects walk at their usual self-selected walking speed on a length of $4m$

level ground at each subject’s self-selected comfortable speed while using a wheeled walker; and 3) walking on a motorized medical treadmill [93].

The dataset presented in [94] contains data acquired by two wearable IMUs laterally attached to the shoes of 15 subjects (11 healthy subjects and 4 PD patients). The used sensors contain a three-axis gyroscope and a three-axis accelerometer. Spatio-temporal parameters have been calculated from the raw signals and validated by using a reference camera-based markerless motion capture system, opportunely synchronized with the wearable sensor system. The same IMU sensors, mounted laterally to the heel of the subject’s right and left shoes, have been used in [95] for recording gait data (acceleration and orientation data) from 40 elderly controls (age 50-75), 15 patients with PD (age 55-80) and 15 geriatric patients (age 75-85). Subjects perform 2 protocols: a straight $40m$ walking test at self-selected speed and 2 minutes free walk containing different walking conditions (stair climbing, straight walk, walk in curves and so on).

Contrary to the previous datasets, an ambient system has been used in [96] for deriving gait spatio-temporal parameters and joint kinematics of 65 healthy subjects, 19 patients with CA, 26 with HSP, and 32 with PD. The system is a frame-by-frame MCS that has been used for recording 3D marker trajectories. Marker position data have been processed for calculating the spatio-temporal parameters and joint kinematics. These parameters as well as anthropometric and clinical characteristics of subjects are listed in [96].

An instrumented walkway (GAITRite®) and inertial sensor-equipped shoes have been used in [97] to measure spatio-temporal parameters and heel strike, toe off angles and foot clearance. Hospitalized patients were included in an observational study and subjected to instrumented gait analysis at the Geriatrics Centre of the Waldkrankenhaus St. Marien, Erlangen, Germany. One hundred six patients (ages 68-95), with signs of gait and balance impairment, performed the gait test with and without gait support from a wheeled walker.

A further dataset for human gait analysis is presented in [98], where a population of 44 older adults (ages 61-78) were asked to walk ten times between two points at a distance of $12m$ apart and to perform additional mobility tests such as the Short Physical Performance Battery. Kinematic data were collected using a Vicon MCS. The spatial and temporal gait parameters were calculated using the Nexus 2.9.3 software.

The *GAITRite®* walkway system has been used also by the Biomathics consortium, in the so-called “Gait, cOgnitiOn & Decline” (GOOD) initiative, to collect spatio-temporal gait parameters [99], involving more than 2700 participants with and without dementia. The consortium connects academic research teams on aging and longevity for promoting health. It shares knowledge and data collected by various international clinical research groups, making available the largest database in this field of research [101], [102].

To the best of the authors’ knowledge, vision-based datasets, in the context of gait analysis of patients affected by NNDs, are not publicly available. Researchers, usually, build their own datasets based on video data that are private. Moreover, privacy issues must be considered in this particular context. In [100], a dataset built starting from video data is provided. In order to preserve privacy, only skeletal information of people, aged 60 years and older, is given, while they perform three well-established mobility tests, including walking. Skeletal data are obtained applying OpenPose library [103] to video images acquired by using a setup of three monocular cameras. Participants are 27 healthy people and 20 patients affected by neurodegenerative diseases, housed at two different nursing institutes.

Further datasets collecting data on gait, by using non-wearable sensors, are available in the literature but do not refer to people suffering from a neurodegenerative disease. However, they are noteworthy as they can be used for deriving clinical endpoints that can potentially indicate the onset of a disease. The most commonly used are: the CASIA Gait Database [104], the Long Term Movement Monitoring database [105], the Georgia Tech Database [106], the CVPR Gait Dataset [107], the UTKinect-Action3D [108], the OU-ISIR Gait Dataset [109], SDU-Gait Dataset [110]. These datasets consist of various videos and data of subjects performing different actions, including walking, in indoor and outdoor settings. These datasets provide the scientific community with a test-bed for testing and improving algorithms in order to extract and recognize features useful to study gait, stability, and fall risk and to classify gait disorders [72].

VII. Gait Features

The goal of gait analysis in elderly people and in particular in elderly people affected by neurodegenerative diseases is to capture motion variations. These variations, such as postural instability or slowness of movements, are very important for evaluating the evolution of the disease. The aim is to extrapolate the best features that characterize these variations in order to detect gait abnormalities imputable to the disease and contribute to timely diagnosis and clinical management. So, gait analysis involves the measurements of several features which can be defined as spatio-temporal, kinematic, and kinetic features [111]. Spatio-temporal features are principally related to distance measurements of various parts of the body during the walk and to the duration of the different phases of gait. Kinematic features refers to the angular excursions formed at body joints caused by rotatory motions of body segments. Kinetic features relate to the force causing the motion of legs and feet during walking so they provide information about joint moments and powers. In Table III a more comprehensive description of these features is given together with the typical sensors used for their measurement. Indeed, different features can be measured by different sensors, so their measurement and reliability are strictly related to the used sensors. In the following subsections, the listed types of features that have been studied over the years will be analyzed.

A. Spatio-Temporal Features

Spatio-temporal features are undoubtedly the most used for gait analysis and have been extensively studied and tested over the years [29], [65], [66], [102], [112]. As can be seen in Table III, with spatio-temporal features we mean a set of parameters that can be calculated starting from distance and time measurements involved during the gait cycle: step length, step width, times of stance, swing, single and double support, step number, stride length and duration, times of heel strike, toe strike, heel-off and toe-off, and so on. The great diffusion of this typology of features resides in their elevated versatility: it is possible to extrapolate spatio-temporal features in different ways, giving therefore the possibility to exploit the application of various types of technologies from wearable to ambient sensors.

Wearable sensors, such as accelerometers or gyroscopes, are the most used devices for capturing spatio-temporal features. In [38], spatio-temporal features, measured from a single accelerometer, are studied in order to identify the optimal ones for aiding the diagnosis of PD. In particular, classification experiments are carried out considering spatio-temporal features alone (with an accuracy of 70.42%), spatio-temporal features combined with signal-based ones (with an accuracy of 86.65%), and with demographic data (with an accuracy of 88.73%). Signal-based features are estimated by using signal processing techniques in time and frequency domain (signal magnitude, regularity, complexity, smoothness and symmetry). The study highlights how signal-based characteristics add greater classification value to support early identification of PD, compared to traditional spatio-temporal features alone. Demographic data, such as aging height, body mass and gender, also, affect gait variability and then intervene in discerning pathological anomalies, even if with a lower increase in classification performance.

TABLE III
LIST OF FUNDAMENTAL GAIT FEATURES.

Feature Type	Sensors	Feature Name	Feature Definition
Spatio-Temporal [29], [38], [65], [66], [102], [112], [113], [114], [115]	Accelerometer, Vision, IMU, MCS	Step Length Stride Length Step Width Step Time Stride Time Stance Time Swing Time Single Support Time Double Support Time Cadence (steps/min) Step Velocity (cm/sec)	Distance between the heel contact of one foot and the heel contact of the other foot Distance between two successive heel contacts of the same foot Distance between feet, while walking Time duration to complete one step Time duration to complete one gait cycle Time duration of stance phase Time duration of swing phase Time duration of single support phase Time duration of double support phase Number of steps taken in one minute Ratio between distance and time (Step Length/Step Time)
Kinematic [35], [36], [39], [65], [116], [117]	Gyroscope, MCS, Vision	Hip Angle Knee Angle Ankle Angle Mean pelvic tilt Foot progression angle	Angle between the thigh axis and the trunk axis (in sagittal plane) Angle between the lower leg axis and the thigh axis (in the sagittal plane) Angle between the sole axis and the lower leg axis (in the sagittal plane) Angle created by a line running from the sacral endplate midpoint to the center of the bifemoral heads and the vertical axis. Angle between the line from the calcaneus to the second metatarsal and the line of walking progression
Kinetic [60], [118], [119], [120]	Force Plates, Pressure Insoles, Instrumented Walkway	Hip Extension/Flexion Moment and Power Knee Extension/Flexion Moment and Power Ankle Dorsiflexion/Plantarflexion Moment and Power	Joint moments used to obtain an estimate of total load on muscles, ligaments, or bones around a joint

Investigations on the identification of the most valuable temporal feature sets for the classification of neurodegenerative patients and healthy control subjects are presented in [113]. Ten temporal features are extracted from patient gait cycles by using the Gait in Neurodegenerative Disease Database. Four feature selection methods (namely the maximum signal-to-noise ratio based feature selection method, maximum signal-to-noise ratio combined with minimum correlation-based feature selection method, maximum prediction power combined with minimum correlation-based feature selection method and principal component analysis) are proposed and tested achieving classification accuracy ranging from 79.04% to 93.96%. Reducing the number of features to four (right stance, double support, right swing, and left swing) continues to maintain relatively high classification performance.

Also in [114], investigations about the search of the best set of spatio-temporal features, in detecting the presence of a gait disorder, are presented. Sixteen features are extrapolated through the analysis of videos obtained with a system of eight infrared cameras. These features are tested as a whole or are reduced in as many subsets as possible (permuting the original 16 features), with the aim of identifying the best subset of most informative features for each of the seven classifiers used. Analyzing the features able to discriminate among diseased and healthy subjects, it is found the importance of step length, swing speed, and cadence in detecting the presence of a gait disorder. Furthermore, reduced sets of 3, 4, or 5 features are sufficient to achieve high classification accuracy ranging from 93.6% to 98%.

Spatio-temporal features can be, also, extrapolated from pressure pads, usually used in hospital settings. In [115] a set of 9 spatio-temporal features, extracted by using simultaneously two instrumented platforms and the Vicon MCS, has been tested with the aim of highlighting which features are the most significant for the classification of PD patients and controls. Features have been analyzed in both raw and normalized form with five machine learning classifiers. Two different normalization approaches have been applied: Dimensionless Equations and Multiple Regression. Classification accuracy of PD is lowest when using raw data with a mean classification accuracy of less than 80%, and highest in the case of Multiple Regression normalization, with a mean classification accuracy ranging from 82% and 92.6%. Significant differences in spatio-temporal features between PD and controls have been observed in stride length and double support time in the case of using raw data; stride length, step length, and double support time after normalization by using Dimensionless Equations; and stride length, cadence, stance time, and double support time when normalizing data using the Multiple Regression method. Correlations of the spatio-temporal features (before and after normalization) with speed, age, height, gender, and body mass are also investigated. The study proves that Multiple Regression normalization improves the performance of the classification of PD.

A different way of analyzing pressure data returned by an instrumented walkway for classifying HD severity (low or high) is presented in [60]. Low-level pressure data are transformed into Footprint image patterns. The goal of the work is to show how the use of only low-level features can reach a good level of classification performance with respect to traditional high-level features, such as stride length or step length and so on. The classification has been carried out by using two different techniques and comparing the results when only footprint image data or high-level features are used. In the first case, the best accuracy is 89%. Considering the difficulty of classifying different stages of a disease, this result is noteworthy in the field of gait analysis, as it paves the way for the use of easy-to-extrapolate features, which would allow a significant reduction in computational time.

B. Kinematic Features

Kinematic analysis of gait includes the study of joint angular excursions. More specifically kinematic features are defined as the magnitude of rotatory motions of body segments in the sagittal plane, within a gait cycle [65], [116], [117].

Kinematic features include the so-called Range of Motions (RoMs) which are usually calculated by using wearable IMU sensors located in the lower and upper parts of the body or MCS devices that allow for three-dimensional motion analysis. From the perspective of gait analysis, the most significant kinematic features are the angular values of the ankles, knees, hips and chest. These are evaluated when the maximum flexion/extension of these body parts happens, expressing the real variation of joint functionality.

In [117] comparisons of RoMs with spatio-temporal features are provided for the classification of PD patients and controls. Eight IMU sensors, located on the lower parts of the body are used for feature measurements. Different combinations of features are tested: the entire set of 87 features (both RoMs and spatio-temporal ones) and twelve subsets of different combinations of them. Each of these feature sets has been tested by using different classification algorithms obtaining average classification accuracy ranging from 63% to 96%. Furthermore, additional tests have been carried out reducing the number of IMU sensors and considering only RoMs features of the knees. In this case, more accurate results than those obtained considering only spatio-temporal parameters, have been achieved.

Interesting investigations and comparisons among spatio-temporal and kinematic features are also presented in [65], with the aim of studying the influence of specific cognition aspects on gait patterns. A MCS has been used to measure both spatio-temporal and kinematic features during walking of a group of patients affected by different cognitive disorders and a group of control subjects. The studies, carried out in single- and dual-task paradigm, show that the kinematic data relative to the angular excursion of thigh, knee and ankle, have a leading role in revealing gait impairment than the spatio-temporal parameters alone.

The kinematic study of gait involves further parameters, namely body oscillation, gait symmetry, minimum and maximum acceleration of each stride, stride to stride variability, gait smoothness, gait intensity [36], [35], [39]. These parameters are usually measured by using IMU sensors. In [39] these sensors are placed on the shoes of the subjects under examination. The aim of the work is to select the most informative features for differentiating between PD patients and healthy subjects. Different classification algorithms are applied first on the original set of 32 features thus on reduced feature sets obtained by applying a feature selection technique called Maximum Information Gain Minimum Correlation. The classification accuracy improves from 96.7% achieved by using the original feature set, to 100% in the case of using the reduced set of only 8 features. This study proves that the different measures of gait variability play a distinct role in discriminating the groups of people under examination, and the search for an optimal set of features (dimensionality reduction) can give better results in terms of classification performance.

C. Kinetic Features

Space-time and kinematic features quantitatively describe the abnormalities of gait and usually, are considered the main outcome of gait analysis as they are directly related to how the movements of body or body parts happen. Kinetics adds essential information as it is related to the causes of abnormal movements, namely the forces acting on the body [118]. Indeed, kinetic features are essentially the moments and powers of joints. In the context of gait analysis, the typical joints considered for a kinetic study are those of the lower limbs: ankle, knee and hip.

Kinetic data are usually evaluated by using force and pressure sensors equipped in platforms, instrumented walkways, shoes, or insoles. As described in section IV and VI, this type of sensors measure ground reaction forces exerted by the ground during walking.

In [119] VGRF measures, are used to classify PD patients and healthy control subjects. Only four features are extracted from the available set of measures provided for each foot. The objective of the study is to prove the effectiveness of this type of features in the field of gait analysis for the diagnosis of neurodegenerative diseases. Two different classification techniques are applied, obtaining an accuracy of about 96.39%.

A more recent study [120], extracts the features from the VGRF signals, for the detection of various neurodegenerative diseases at different stages from early to advanced. In particular four statistical moments, describing amplitude distribution of the force under a foot during a complete gait cycle, are evaluated as they better characterize abnormal trembling movements in neurodegenerative diseases. These include: mean, standard deviation, skewness and kurtosis. Furthermore, approximate entropy is also extracted in order to obtain a useful characterization of the irregularity of movement and thus to enhance detection performance. A combination of both statistical and entropic measures extracted from left and right feet, as well as full feature sets, are considered as input data to three different classification methods yielding high average detection accuracy ranging from 93.89% to 100%. The results prove the validity of the proposed features showing high range accuracy rates, achieved even by using only one-foot VGRF signals. This is an important outcome that provides a good trade-off between computational complexity and detection performance.

VIII. Classification

In the last years, Machine Learning strategies in gait analysis have gained great popularity, as they offer the possibility of building automatic systems able to distinguish healthy subjects from patients affected by neurodegenerative diseases or to detect the different levels of the disease from early to severe stage. Once feature extraction and feature selection are carried out, machine learning classification techniques can be applied in order to automatically construct models and then to use them for predicting the likelihood that new data will fall in pre-defined target classes. Plenty of literature works aims to find the best combination of features and classification methodologies for optimizing the process of disease identification/evolution. To this aim, a variety of classification approaches have been applied in literature, including k-Nearest Neighbour (kNN), Naïve Bayes (NB), Linear Discriminant Analysis (LDA), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Neural Networks and Deep Neural Networks, just to name a few. The main challenge is to find the best combination of features and classifiers in order to achieve the best classification rate. In the following, the most widely used classification approaches will be analyzed reviewing works that mainly address this issue. Table IV summarizes these works, listing the classification task, the type of sensors and features, the number of individuals involved in the study, the used classifiers together with the best accuracy obtained within the conducted study and some notes about the used approach.

A. SVM

The Support Vector Machine (SVM) is one of the most widely used supervised learning classifiers in the field of gait analysis. Formally SVM constructs a hyperplane that best separates the samples of the two classes under examination. The aim is to find the maximum margin hyperplane, the one that maximizes the distance between the so-called support vectors, i.e. the samples closest to the hyperplane. The search for this hyperplane can be performed both linearly or non-linearly depending on the type of chosen kernel functions. Kernel functions are, indeed, used to map the data into a higher-dimensional feature space to find the best hyperplane that better separates the two classes.

Non-linear SVM, based on Radial Basis Function (RBF) kernel, is used in [121] for classifying PD patients from two other NDDs (HD and ALS). Various tests applying SVM on different sets of statistical features based on temporal gait parameters are performed in order to achieve the best classification accuracy. The final chosen classifier reaches an accuracy of 83.3% on a set of 7 best features. Analogously, in [113], non-linear SVM with RBF kernel is used to solve 7 binary classification problems distinguishing among three different NDD patients (PD, ALS, HD) and between NDD patients and healthy subjects. Different feature selection and construction methods are applied on a set of 10 temporal features, in order to find the most valuable ones for improving classification performance. SVM, in this case, provides a classification accuracy ranging from 79.04% (case of PD vs. HD) to 93.96% (case of ALS vs. Healthy controls). SVM has been also used and compared to RF in [122] for classifying people with moderate MS (MS-mod), people with mild MS (MS-mild) and healthy controls. SVM performed best at distinguishing healthy controls from subjects with MS-mild and MS-mod, whereas the RF was marginally better at separating MS-mild vs. MS-mod.

Linear and non-linear SVM with RBF kernels are used in [117] on various groups of spatio-temporal and RoM features for PD identification. Non-linear SVMs outperform the linear ones obtaining a classification accuracy of 75.6%. The superiority of non-linear SVM is also investigated considering other types of classifiers on the same set of features obtaining lower average accuracy: k-Nearest Neighbour (73%), Naïve Bayes (72.7%), Linear Discriminant Analysis (72.5%) and Decision Trees (68.8%). In order to improve performances two meta-classifiers are built as a weighted combination of the individual classifiers, applying a Majority-vote approach. This provides a significant improvement in obtaining an accuracy higher than 80%. Additional tests are carried out using SVM RBF for classifying three different stages of PD patients. Accuracy higher than 90% is obtained depending on the specific group of considered features.

Similarly in [52], non-linear SVM shows the best performance with respect to linear SVM, RF, kNN, and DT. Different kernels (linear, Gaussian, quadratic and cubic) are used to train SVMs on Spatio-Temporal and Kinetic features obtained from VGRF signals. Among kernels, the cubic one shows the best accuracy of 95.7% in classifying PD patients and control subjects, proving the important role of CoP as a discriminative feature. Higher classification accuracy has been also obtained in [75] by SVM (99.1%) with respect to RF, Ada Boost and kNN. Kinematic features computed from joint coordinates of human skeletons extracted from video captured by standard RGB cameras have been used.

B. Instance-based methods

Instance-based learning methods base the classification process directly on the training samples, instead of creating a model from specific instances. They simply store all data and each new sample is classified in relation to a predefined query answer obtained from the examination of data. K-Nearest Neighbour and Non-Negative Least Square (NNLS) belong to this family of learning techniques. kNN is one of the less complex classification algorithms as it is based on the principle that instances with similar properties in a dataset will remain in close proximity. So a test sample is classified considering the most common class label among those of the "k" neighbor instances. The choice of "k" is therefore very important as if it is too small, the classification could be "blind" in the sense that important instances could be not considered in the classification process; on the other hand, if "k" is too large very distant instances could be included in the evaluation even if they are very dissimilar with respect to the test sample. In [123], kNN are used for detecting the presence of MCI in PD patient. Spatio-temporal features are evaluated in three different conditions: normal gait, motor dual task and cognitive dual task. kNN achieves the accuracy of 83.8% and a sensitivity of 88.2%, in identifying PD patients with MCI during the gait task, supporting the existence of specific connections between gait and cognition. Considering the dual tasks, instead, kNN performance gets worse, whereas DT reaches an accuracy of 86.8% in the case of motor dual task and RF gets an accuracy of 85.3% in the cognitive dual task, respectively. Similar comparison among different classification techniques including kNN are shown in [117] and [52].

NNLS is a fast instance-based learning algorithm which predicts the class label of unknown samples through a sparse non-negative linear combination of few training samples [124]. After the computation of the coefficients of this combination, class labels are assigned to new samples by using an interpreter. Commonly used interpreters for NNLS are the Max rule and the Nearest-subspace rule. In [120] sparse NNLS, with both aforementioned interpreter rules, has been tested in combination with kinetic features extracted from VGRF signals for distinguishing different NDDs (ALS, PD, and HD) both at advanced and early stages. Tests have been carried out considering three combinations of features extracted from the left and right feet as well as the full feature set. The proposed method recognizes accurately ALS, PD, and HD from healthy controls, achieving 100%, 99.78%, and 99,9% classification accuracy, respectively when considering the full feature set. High accuracy rates (higher than 99%) are also obtained when only the set of NDD patients is considered (PD vs. HD, PD vs. ALS, and ALS vs. HD) and also when they are grouped in early and advanced sets in relation to the disease severity. Furthermore, the proposed method has been compared with SVM and Multilayer Feed Forward Neural Network (MLFNN) classification methods, proving its superiority. NNLS shows its efficiency and robustness in NDDs detection over different stages, combined with either left and right VGRF based features. In Table IV, the accuracy rates regarding the case of a full feature set are reported.

C. Naïve Bayes

The Naïve Bayesian classifier is a selective classifier based on Bayes Theorem and theorem of total probabilities. A complete Bayesian classifier requires knowledge of the a priori and conditional probabilities related to the problem under consideration. Naïve Bayes is a simplified version compared to a complete Bayesian classifier, as it is based on the assumption of conditional independence among the features. The algorithm would produce optimal results if the assumption of independence of the features were actually verified, but it has been shown that the algorithm produces good results even in many practical problems. Naïve Bayes has also been applied in the field of recognition of neurodegenerative diseases through gait analysis. In particular, it has been used in combination with both kinematic features as in [39] or a combination of space-time features and RoMs as in [117] obtaining accuracy values ranging from 83.1% to 90% and from 59.74% and 78.02%, respectively. The obtained accuracy values are lower than those obtained by other classifiers (see Table IV), highlighting that the assumption of feature independence has a strong impact on NB classifier performance. Both cited works, indeed, consider different groups of features in order to find those that better distinguish PD patients from healthy subjects. The fluctuations of accuracy values can indicate a more or less feature correlation within each considered group.

D. Decision Tree, Random Forest, Gradient Boosted Tree

Decision Tree (DT), Random Forest (RF), and Gradient Boosted Tree (GBT) are the so-called tree-based algorithms. The Decision Tree is the simplest one that essentially resembles a sort of decision-making diagram composed out of the root-node, several tree-nodes and leaves. The classification of a sample is accomplished starting from the root node and following the tree-nodes on the basis of the truthfulness of the condition expressed at each node. So a leaf node can be reached to represent the prediction for the current sample. RF and GBT are ensemble techniques that combine a large number of trees, each trained on a randomly selected subset of features. At the end of the process, an RF combines the results by averaging or by using “majority rules”. The RF builds all trees simultaneously and independently. GBT, instead, builds one tree at a time incrementally using the information of the previously built ones to improve the accuracy.

The RF method with the majority rule has been used in [126] for classifying PD patients and healthy subjects. The algorithm produced a very high classification accuracy of about 98.04% when the complete set of time and frequency domain features, extracted from VGRF signals (Gait in Parkinson’s Disease Database), are used. Similarly, RF and DT are used in [52] for the recognition of PD patients, obtaining a relatively high classification accuracy: 89.4% and 87.21%, respectively. In this case, spatio-temporal and kinematic features are extracted from the VGRF signals from a subset of the Gait in Parkinson’s Disease Database considering 28 PD patients and 18 age-matched controls during normal level ground walking for two minutes [92].

RF and GBT have been also chosen in [66], to test a problem more complex than the binary classification of PD patients and healthy subjects. The aim is to recognize different stages of PD disease, in order to optimize therapies. The classifiers were tested in combination with spatio temporal features measured by using a MCS and pressure platforms. RF exhibits the overall highest accuracy of 86.4%, but also GBT achieves an accuracy of 84% that can be considered a good result especially considering the high level of complexity. A similar complex problem is considered in [123], where the aim is to differentiate between PD patients with and without MCI. Furthermore, single gait task and dual task conditions (motor and cognitive) are compared. Both RF and DT, trained on spatio-temporal features obtained by using a MCS and two force plates, exhibit comparable performance achieving accuracy of 76.5% and 75%, respectively. Higher accuracy rates are obtained in [39] by applying RF on kinematic features for distinguishing PD patients from healthy controls and geriatric subjects. The accuracy range from 83.3% and 100% depending on different groupings of features. The best performance is achieved in the case of only 8 discriminative features.

E. Multilayer Feed Forward Neural Networks

Multilayer Feed Forward Neural Networks (MLFNNs) are artificial neural networks capable of identifying complex non-linear relationships between input and output data. They are composed of an input layer, one or more hidden layers, and an output layer of nodes. Different activation functions can be used at nodes (except for the input nodes) for mapping

TABLE IV
LIST OF CLASSIFIERS WITH ACHIEVED ACCURACY.

Ref.	Classification Task	Feature Type (Database)	Classification Technique (Accuracy)	Sensor Type	Sample Size	Notes
[113]	NDD vs. Healthy ALS vs. PD ALS vs. HD ALS vs. Healthy PD vs. HD PD vs. Healthy HD vs. Healthy	Temporal (Gait in Neuro-Degenerative Disease Database)	SVM RBF (86.85%) SVM RBF (85.47%) SVM RBF (86.52%) SVM RBF (93.96%) SVM RBF (79.04%) SVM RBF (86.43%) SVM RBF (84.17%)	Force-Sensitive Resistors (VGRFs)	PD=15; HD=20; ALS=13; Healthy=16	Average computational cost; Need of instrumented shoes; Lack of upper body movement analysis.
[120]	NDD vs. Healthy NDD vs. Healthy NDD vs. Healthy ALS vs. PD ALS vs. HD PD vs. HD	Kinetic (Gait in Neuro-Degenerative Disease Database)	NNLS (96.57%) SVM (80.20%) MLFNN (93.53%) NNLS (99.26%) NNLS (99.06%) NNLS (99.11%)	Force-Sensitive Resistors (VGRFs)	PD=15; HD=20; ALS=13; Healthy=16	Average to high computational cost; Need of instrumented shoes; Lack of upper body movement analysis.
[121]	PD vs.NDD	Temporal (Gait in Neuro-Degenerative Disease Database)	SVM RBF (83.3%)	Force-Sensitive Resistors (VGRFs)	PD=15; HD=20; ALS=13; Healthy=16	Low computational cost; Need of instrumented shoes; Lack of upper body movement analysis.
[125]	PD vs. Healthy	Spatio-Temporal and Kinetic (Gait in Parkinson's Disease Database)	RBF-NN (98.8%)	Force-Sensitive Resistors (VGRFs)	PD=92; Healthy=73	Average computational cost; Need of instrumented shoes; Lack of upper body movement analysis.
[126]	PD vs. Healthy	Spatio-Temporal (Gait in Parkinson's Disease Database)	RF (98.04%)	Force-Sensitive Resistors (VGRFs)	PD=92; Healthy=73	Average computational cost; Need of instrumented shoes; Lack of upper body movement analysis.
[52]	PD vs. Healthy	Spatio-Temporal and Kinetic (Subset of Gait in Parkinson's Disease Database)	non-linear SVM (95.7%) linear SVM (91.6%) RF (89.4%) kNN (85.1%) DT (87.21%)	Force-Sensitive Resistors (VGRFs)	PD=29; Healthy=18	Average computational cost; Need of instrumented shoes; Lack of upper body movement analysis.
[117]	PD vs. Healthy PD vs. Healthy PD vs. Healthy PD vs. Healthy PD vs. Healthy PD vs. Healthy PD severity	Spatio-Temporal and RoMs (Private Dataset)	SVM RBF (75.6%) linear SVM (72%) K-NN (73%) NB (72.7%) LDA (72.5%) DT (68.9%) SVM RBF (>90%)	IMU sensors (accelerometer, gyroscope and magnetometer)	PD=27; Healthy=27	Average computational cost; Need of wearing IMU sensors; Sensible to interferences.
[60]	HD severity	Footfall pressure Footfall and spatio-temporal Footfall pressure Footfall and spatio-temporal (Private Dataset)	SVM (76.9%) SVM (86.9%) VGG16 (89%) CNN (82%)	Walkway system (Pressure data converted to RGB images of footprints)	HD=6; Healthy=6	Lack of upper body movement analysis; High computational cost; Limited dataset.
[66]	PD severity	Spatio-Temporal (Private Dataset)	RF (86.4%) GBT (84%)	MCS	PD=46	Need of the installation of MCS; High cost of MCS; Average to high computational cost.
[123]	MCI in PD	Spatio-Temporal (Private Dataset)	K-NN (83.8%) DT (75%) RF (76.5%)	MCS	PD=22; PD with MCI=23	Need of the installation of MCS High cost of MCS.
[39]	PD vs. Healthy and Geriatrics	Kinematic (Dataset by Barth et al. [95])	K-NN (83.8%) NB (90%) SVM (83.6%) RF (100%) AdaBoost (100%) Bagging (96.7%)	Two IMU sensors laterally attached to the shoes	PD=10 Healthy=10; Geriatric Subjects=10	Limited dataset; Average computational cost; Need of wearing IMU sensor; No inter-subject separation scheme; Lack of upper body movement analysis
[127]	AD severity	Kinematic (Private Dataset)	CNN (91%)	Three-axis accelerometer	AD=35	High computational cost; Need of wearing IMU sensor; Lack of upper body movement analysis
[128]	Fall Risk Assessment (NDD patients)	Kinematic (Private Dataset)	LSTM (92.1%) RF (84.3%) MLFNN (90.3%) SVM (83.3%)	IMU sensors installed in shoes	76 PD patients divided into two groups according to their fall history	High computational cost; Need of wearing instrumented shoes; Lack of upper body movement analysis.
[122]	MS-mild vs. Healthy MS-mild vs. Healthy MS-mod vs. Healthy MS-mod vs. Healthy MS-mild vs. MS-mod MS-mild vs. MS-mod	Spatio-Temporal (Private dataset)	SVM (66.4%) RF (63.2%) SVM (82.2%) RF (76.2%) SVM (82.3%) RF (84.0%)	Three-axis accelerometer and gyroscope in smartphone and smartwatch	MS-mild=52; MS-mod=21; Healthy=24	Use of off-the-shelf hardware; Limited computational cost; Lack of upper body movement analysis.
[75]	NDD vs. Healthy	Kinematic (Private Dataset)	SVM (99.1%) RF (94.2%) Ada Boost(93.2%) kNN (94.9%)	Standard RGB cameras	NDD=20; Healthy=20	All body parts under analysis; Low costs; Need of installing ambient sensors.

the weighted inputs to the output of the node. MLFNNs have been tested for PD disease classification in [55] over different types of input features: spatio-temporal, kinetic and kinematic evaluated from VGRF signals. A deep analysis of the impact of the different sets of features is carried out in order to find the best subset of features that better differentiate PD patients from healthy controls. The best classification accuracy of 95.63% is obtained when four significant features are selected via statistical analysis.

In [125] Radial Basis Function Neural Networks (RBF-NNs) are used for the classification of gait patterns between PD and healthy control subjects. RBF-NNs are a specific case of MLFNNs, where the activation functions are represented by the radial basis functions. In this case, data interpolation is commonly done by means of Gaussian curves and therefore tends to be more precise. The features used in [125] are extracted by VGRFs from the Gait in Parkinson's Disease Database. In order to get a more efficient feature set, a feature extraction scheme is proposed based on phase space reconstruction and empirical mode decomposition preserving differences in gait dynamics. Classification is then carried out by applying RBF-NN on the obtained features and considering three cross-validation methods. The classification accuracy ranges from 91.46% and 98.8%. Other more recent works apply MLFNN on a different type of input data prevalently for comparison purposes with other state-of-the-art learning methods [120], [128].

F. Deep Learning

Recently Deep Learning has received increasing attention in several pattern recognition domains and so in gait analysis. Deep learning techniques have the great advantage of avoiding handcrafting feature extraction methods as they implicitly find discriminating regularities in the raw data. The most popular deep learning method is Convolutional Neural Network (CNN) usually used to analyze imagery data, but suitable for different data sequences. CNN consists of a fully connected neural network structure with several hidden layers, pooling layers, and normalization layers, with a set of filters and weights shared among these layers. CNN can recognize hierarchies of patterns from smaller and simpler ones without increasing the model complexity.

In [60], two types of CNN architectures have been compared for analyzing the footprint pressure images obtained from an instrumented walkway for classifying HD patient disease severity (high and low). The aim is to prove that the footprint images hold rich features and can produce good classification performance even without combining spatio-temporal features. The proposed method combines a pre-trained VGG16 (which is a type of CNN) for feature extraction and a grouping phase based on a weighting procedure. This method applied to the footprint images has revealed good performance obtaining a classification accuracy of 89%. For comparisons, two additional tests have been carried out by applying SVM to both footprint images only (76.9% classification accuracy) and a combination of footprint images and spatio-temporal features (86.9% classification accuracy). This proves that SVM does not work properly with pressure frames, whereas it seems to be more appropriate for working with high-level features. The results show that CNN gets worse performance when high-level features are fused with the image-based ones.

In [127], a CNN is used to classify AD severity stages (early, middle, and late) by using records of accelerometer data (acceleration changes in the three directions X, Y, Z along time). Considering the complexity of the classification problem and the presence of complex pattern sequences of mixed length within the movement data, a deep learning method seems suitable for managing this data as it takes advantage of the internal structure of data sequences. Therefore CNN has been chosen as a classification method obtaining high accuracy rates for the three classes: 89% (early AD), 93% (middle AD), and 91% (late AD).

A more recent work [128] explores the applicability of deep learning to the complex and challenging problem of fall risk inference in patients with PD. In this case, the Long Short-Term Memory (LSTM) deep neural network has been applied on sequences of spatio-temporal gait parameters measured by IMU sensors attached to the dorsum of both feet. Raw data are properly pre-processed in order to construct sequences of gait capturing both temporal variations and asymmetries in gait. LSTM network has the advantage of remembering long-term dependencies within the data. In this case, a bi-directional LSTM has been used which is suitable for a sequence-to-label classification mode of operation. Classification accuracy of 92.1% has been achieved by LSTM. Additional comparisons with traditional classification methods (SVM, RF, MLFNN) are also presented.

IX. Discussion

Instrumented evaluations of gait parameters, thanks to the accuracy, repeatability and reproducibility of the measurements, can undoubtedly support specialists in making objective diagnoses. The literature review, carried out in this article, has revealed a number of problems and challenges.

A. Sensors and protocols

The first point concerns the selection of sensors, among the large variety of possibilities, that depends on the specific aim of the research task, the set of parameters to be monitored, the physical and use-case constraints, the available budget, the extension of monitoring in terms of space and time. At the time of writing, there is not a technology able to meet all the desired requirements. Reviewed papers reveal that an accurate pose estimation requires, in general, expansive and distributed sensors within a very controlled environment and for a limited time. Accurate evaluations have been obtained with ambient sensors such as floor sensors, force platforms, electronic walkways or motion capture systems, while subjects walk on clear and specific defined walkways under the real-time control of specialists. The results are collections of data linked to specific observation periods. If by the one hand these sensors provide precise and in-depth studies, on the other hand they cannot be applied to "into-the-wild" (or real-life) gait analysis outside the instrumented environment.

A recent trend deals with the investigation of gait analysis with optical sensors. RBG, RGB-D, Stereo, Structured Light, Infrared cameras can provide different types of images that can be used to extract gait parameters. To date, vision-based sensors are probably the most viable solution for wide monitoring aims offering different solutions within multiple budget ranges. Furthermore, the research in the image/video processing field has led to an important improvement in body tracking capabilities provided as comprehensive and free tools in out-of-the-box software development kits. These technological developments, difficult to foresee only one or two years ago, will lead to results of sure significance for the scientific advancement in the field of gait analysis. Moreover, apart from controlled environments, these systems could be easily installed in private environments and could capture important and impactful data not only related to gait but also to posture or daily activities in order to have a complete clinical model of the person under analysis.

Regarding wearable sensors, overall results are interesting, however, all the reviewed studies stressed the strict relation between the quality of acquired data and the final accuracy of the system. In other words, due to the kind of sensor and the body part on which the sensor is worn, many calibration steps are required. Of course, technology advancements will improve performances and make it possible to build increasingly miniaturized devices that can be placed into clothes (smart garments) for uncontrolled and long-term observations of individuals thus solving the problem of forgetting to wear the device. In this case, combined systems based, on wearable sensors and Human Activity Recognition (HAR) modules, could be very helpful for a contextual study of gait. If people walk while they are performing other tasks (e.g. carrying objects), combined systems of gait analysis and HAR would give the possibility to capture gait-related parameters and other useful information in order to reveal specific events such as fall, supine or sit position, and so on. Also energy management in wearable devices, which had been considered for a long time one of the main drawbacks of this technological category, is in continuous improvement as a result of the development of low power/energy demanding electronics. In addition, new recharging capabilities offered by contactless magnetic solutions can aid their implementation in an easier way.

For target users confident with the daily use of technologies (in general expected to be younger than those typically involved in many NDD studies) also smartphones or smartwatches can play a crucial role since they include accelerometers and gyroscopes. Therefore, gait analysis can benefit from the large literature on well-tested approaches that use IMU sensors. Finally, the gradually emerging wireless-based devices for passive sensing can be a further future solution. They have been used for gesture recognition, human activity detection, human body tracking, human body localization, but they have been only marginally investigated in the context of gait analysis in neurodegenerative diseases. Future research will certainly bring valuable results also for gait parameters monitoring.

B. Methodologies, datasets and performances

The analysis of the reviewed articles has revealed that there is not clear evidence on which system or approach is better than the other because different studies have been performed on different and/or limited datasets acquired with different devices and by using different protocols. This prevents the possibility of a clear and fair comparison, but only allows some indications to be drawn. For instance, regarding features, the spatio-temporal ones are the most used, but as can be seen from Table IV classification performance (in terms of accuracy) deteriorates compared to kinetic and kinematic features. Undoubtedly, the joint use of multiple features, regardless of the specific category, allows for better performance.

Regarding classification, known the relation between methodology and data necessary to build the class model, it is possible to draw some conclusions on which methodology should be used according to the kind and quantity of available data. Approaches such as instance-based or tree-based methodologies can provide good classification performance even with little data available, as they base on rules or proximity levels of data. Other methodologies, such as NNs, linear and non-linear SVMs, need to build class separation models and both the quality and the quantity of data can affect the results. However, to date, SVM has been the most used approach to provide medium to high accuracy (depending upon the specific task and feature set). Furthermore, the appropriate combination of feature selection and classification methods together with an abundant quantity of labeled data are fundamental to extract relevant information and train classifiers with generalization abilities. The recent trend of using deep networks, such as CNNs or LSTMs, has led to a new way of analyzing data: classifiers are able to extract features directly from raw data, however, they require a huge amount of data that cannot be always available. Although some evidence is at hand [128], there is no proof that Deep Learning is able to outperform Shallow Learning in this domain.

The availability of data is another important point on which future efforts have to focus: there is an urgent need to create large data sets for developing, testing and comparing data processing approaches. The problem of generating new datasets is related to the availability of a large number of subjects, of proper equipment for data collection, of several executions of the walk, and above all to the knowledge of the disease severity of the subjects under observation. As detailed in table II, available datasets are, in general, limited to few patients and healthy controls while walking along predefined paths for few minutes. These datasets are not sufficient to train advanced machine learning models. In the last years, the large availability in many application contexts of few data, carefully labeled by humans, together with abundant unlabelled data has given a great impulse to the research on semi-supervised methodologies that make predictions on entire datasets to generate pseudo-labels for unlabelled data and train deep neural networks. In human gait analysis, also sharing few available labeled data with the much more unlabelled data would be of great utility for the machine learning scientific community. Another point that emerges from the analysis of datasets is the scarcity of vision-based datasets. Many vision-based datasets are available in the literature for activity monitoring or gait analysis for biometric tasks, but only a few collect data on the gait of individuals with NDDs. As discussed above, the recent improvements of camera-based systems together with the software tools for body tracking will provide a huge quantity of gait data in the next future. Therefore, there is the need to make this data available in order to test methodologies and compare results by using common evaluation metrics.

The rapid aging of the population, the need for home assistance, the increasing demand for telemedicine services, the progress of sensing technologies and the methodological improvements suggest that the future direction of research will be the long-term and free-living monitoring of subjects. This task represents the challenging future direction of research as it could be of fundamental help for revealing changes in gait, postures and habits for several purposes: to detect disease progression, to prevent falls, to improve quality of life, or to prolong the independent living of elderly people. In this new scenario, the long-term uncontrolled gait monitoring in free-living environments yields new opportunities to monitor and understand the mechanisms behind the NDDs. The observation of gait changes, while subjects perform their daily activities, cannot replace instrumented evaluation in controlled laboratory environments, but can reveal several parameters extracted by other behavioral observations (time spent in sedentary behavior, standing, count of sit to stand transitions, the total number of steps for a given period, and so on) that can be very useful to interpret the evolution and the severity of diseases.

X. Conclusions

In this paper, the fundamental issues of gait analysis, for supporting the diagnosis or the progression of neurodegenerative diseases, have been explored. The literature has been reviewed following a sequential thread starting from a panoramic survey of sensor modalities, mainly used for data acquisition, opening a little window on protocols for gait measurements and on the publicly available datasets, going through the description of more significant features up to the final high-level decision support phase, which essentially involves the classification of available data. To date, a large number of gait parameters have been measured by using various technologies and modelled by applying several methodologies in order to better understand impaired gait due to different neurodegenerative conditions. However, the majority of investigations based on studies in clinic environments, small populations suffering from neurological disorders, pre-defined and limited gait protocols. Free-living gait assessment is the new study direction where the scientific communities are going to focus their efforts as it reflects real-life settings, where habitual and insightful gait data can be captured on observed subjects. This is further favored by the continuous progress of both miniaturized wearable technologies and commercial high-resolution optical ambient sensors that will allow for capturing different types of gait characteristics useful for more in-depth free-living gait study. On the one hand, this creates great opportunities in timely detecting gait disorders on a wide range of neurological conditions for contributing to the design of proper interventions. On the other hand, it opens new challenges related to the need of developing standardized approaches for quantifying gait and to the need for synchronizing and fusing multi-sensor data. Furthermore, it is also evident the need for developing fast procedures in order to satisfy real-time requirements. Complex environment management, execution time and complexity reduction, in fact, represent additional challenging factors worthy of further investigations in order to develop efficient, consistent and real-time monitoring systems.

XI. Appendix

The list of abbreviations used in this manuscript.

AD	Alzheimer's Disease
ALS	Amyotrophic Lateral Sclerosis
CA	Cerebellar Ataxia
CoP	Center of Pressure
CNN	Convolutional Neural Network
DT	Decision Tree
HAR	Human Activity Recognition
HD	Huntington's disease
HSP	Hereditary Spastic Paraplegia
kNN	k-Nearest Neighbour
IMMS	Inertial and Magnetic Measurement System
IMU	Inertial Measurement Unit
LDA	Linear Discriminant Analysis
LSTM	Long Short-Term Memory
MCI	Mild Cognitive Impairment
MCS	Motion Capture System
MS	Multiple Sclerosis
MLFNN	Multilayer Feed Forward Neural Network
NB	Naïve Bayes
NDD	NeuroDegenerative Disease
NNLS	Non-Negative Least Square
PD	Parkinson's disease
RBF	Radial Basis Function
RBF-NN	Radial Basis Function Neural Network
RF	Random Forest
RoM	Range of Motion
SVM	Support Vector Machine
VGRF	Vertical Ground Reaction Force

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