Assessment of Robotic Devices for Gait Assistance and Rehabilitation

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13.1 Introduction

In the last decades, the development of robotic devices for gait assistance and rehabilitation has shown ongoing growth [1, 2]. As these technologies have expanded and matured, the need for accurate assessment and understanding of how users perform with the robotic devices has become evident and has been a convergence point for multiple technology designers. Even if robotic technology's potential was and is indisputable, demonstrating its value on a quantitative basis has been challenging. Trying to address this general concern, many research studies have started to evaluate robotic devices' performance, resulting in an abundant and highly diverse compilation of methods, variables, and protocols. The enormous amount of information led the robotics community to increase interest in benchmarking to scientifically assess and compare robotic devices' performance for gait assistance and rehabilitation. Even though benchmarks have been long used to verify and compare the readiness level of different technologies in many domains, not long ago, the primary approach to compare devices like exoskeletons was only through competitions, such as Cybathlon [3]. The big challenge of unifying a benchmark is even more difficult for the specific case of assistive and rehabilitation devices. The intrinsic interaction of these devices with the subjects complicates finding

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appropriate metrics to measure their performance. Hence, studies in this area generally have to be accompanied by performance studies of the subject and not just the robots.

The foundations to build such standards have been laid by recent efforts in the field of benchmarking bipedal locomotion to consolidate a unified scheme for humanoids, wearable robots, and humans [4]. Subsequently, work has been done attempting to organize the available assessment information and identify performance indicators that could be converted into practical benchmarks [5, 6].

This chapter presents an overview of the most promising and used measures, experimental procedures, equipment, sensors, and tools so far identified in the literature to assess gait robotic assistive and rehabilitation devices. The chapter starts with the introduction to the basic concepts to understand the implications and ways to assess the performance of an activity. Thereafter, the different modules towards a correct assessment are explained.

13.2 Motor Skills, Abilities, and Performance

The assessment of robotic devices for gait assistance and rehabilitation is a multi-disciplinary area. Engineers and clinicians of different backgrounds have to agree on common nomenclature and classification systems to conceive standards in the assessment process. Inspired by the approach by Magill [7], further organized and discussed by Torricelli et al. [4], three basic concepts are often used to understand the area: motor skill, motor ability, and motor performance (see Fig. 13.1).

A motor skill, also called action in the motor learning and control research literature, refers to an activity or task that has a specific goal to achieve. However, not all activities with a goal are considered motor skills. To be studied as one, it needs to have other characteristics as: (i) be performed voluntarily, (ii) require the movement of joints and body segments, and (iii) be learned or relearned (as it usually happens in the field of rehabilitation) [7]. The most basic motor skill in this book is walking, but several others will be contemplated in the following sections.

Highly related to the concept of skill is the one of abilities. Motor abilities can be referred to as the general traits of an individual that are a determinant of his achievement potential for the performance of specific skills [7]. Let the skill be walking. The abilities may refer to stability, coordination, compliance, and any other characteristic needed to walk.

The last concept is motor performance, defined as the level of achievement of the goal, i.e., how well the goal established in the skill is achieved. The performance of any motor skill is influenced by (a) characteristics of the skill itself, (b) the environment in which the skill is performed, and (c) the person performing the skill [7], as presented in Fig. 13.1. The person is the agent in charge of learning and adapting the skill through the observation and perception of the performance.

Measuring the level of achievement of a skill is not a straightforward process. Many ways to assess motor performance have been defined over time. These different measuring methods are called the performance indicators (PI) [4] and can

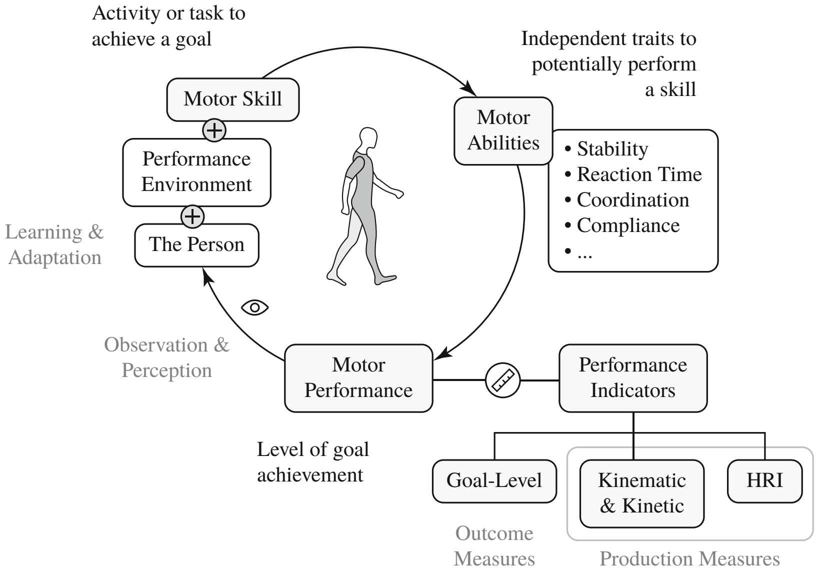

Fig. 13.1 Basic concepts in the assessment of robotic devices that interact with humans

be grouped into two main categories according to Magill. In the first one are the performance outcome indicators, which indicate the result of performing a motor skill (e.g., how far or fast a person walked). They provide information where the primary concern is whether or not the goal of the skill was accomplished. In the second category are the performance production indicators, which indicate how the different human systems (e.g., the nervous system, the muscular system, and the movement of the limbs or joints) function during the performance of a motor skill [7]. This category includes both kinematic/kinetic measures and the ones defined as Human–Robot Interaction (HRI) measures [4], which will be addressed in further sections.

13.3 Classifying Motor Skills

A complete understanding and characterization of related motor skills is crucial to correctly assess the performance of robotic devices used in gait assistance and rehabilitation. Classifying the motor skills for which these devices are developed and the possible variations and conditionals involved is the first step in the assessment process. Several proposals like the ones by Gentile [8] and Fleishman et al. [9] successfully classify motor skills and motor abilities and are commonly used in physical therapy and psychology.

Similar to what was established to influence a motor performance in Fig. 13.1, Gentile classified motor skills according to two general items. The first one is the environment, which he divided into: (i) unaltered motion and (ii) with the presence of inter-trial variability or unexpected disturbances. The second item corresponds to the function of the motor skill, which is classified according to: (i) the motion of the body (posture or transport) and (ii) the simultaneous manipulation of an object during the execution of the task. Furthermore, Fleishman proposed a list of the "fewest independent ability categories which might be most useful and meaningful in describing performance in the widest variety of tasks" [9]. In addition to the abilities previously established as an example for the skill of walking, significant motor abilities from that list are inter-limb coordination, static and dynamic strength, limb flexibility, gross body equilibrium, reaction time, speed of limbs, and control precision [4]. However, Fleishman's lists should not be considered exhaustive inventories of all the abilities related to motor skill performance, as the objective was to identify the smallest number of abilities that would describe the tasks performed [7].

Based on those two taxonomic proposals, a benchmark for bipedal locomotion was created to unify a scheme for humanoids, wearable robots, and humans [4]. The motor skill classification presented here maintains the conventions defined there.

13.3.1 Walking

Walking is undoubtedly the core motor skill to be assessed and the main focus of the robotic devices described in this book. However, since motor skills can be further classified according to: (i) environment variability and (ii) the presence of external disturbances, the relevant motor skills for robotic devices are:

- Walking in a **static** environment with a **constant or absent** disturbance:
  This includes walking on flat ground, constant slopes, ascending or descending stairs, and backward walking.
- Walking in a **static** environment with a **variable** disturbance:
  This includes walking on variable slopes, irregular terrains, and slippery surfaces.
- Walking in a **moving** environment with a **constant or absent** disturbance:
  This includes walking on a constant treadmill, a constant soft ground, and walking while bearing additional weight.
- Walking in a **moving** environment with a **variable** disturbance:
  This includes walking on a variable treadmill, a variable soft ground, when pushed, overcoming obstacles and slalom or turning.

13.3.2 Standing

Even if most of the efforts when designing a robotic device are devoted to walking, standing (maintaining an upright posture) is critical motor skill to assess. Standing is evaluated employing the same two previous variables:

- Standing in a **static** environment with a **constant or absent** disturbance: This includes standing on a horizontal surface and an inclined surface.
- Standing in a **static** environment with a **variable** disturbance: This includes standing on uneven terrains and during manipulation.
- Standing in a **moving** environment with a **constant or absent** disturbance: This includes standing while bearing additional weight and while periodic tilts or moving ground.
- Standing in a **moving** environment with a **variable** disturbance: This includes standing in the presence of pushes and while irregular tilts or rough translations.

13.3.3 Others

Finally, other skills related to the assessment of robotic devices and not included in either of the aforementioned categories can be of value and are covered. This includes activities, where the environment is static and there are no or constant disturbances, such as: lateral stepping, crouching or kneeling, changing from sitting-to-standing or from standing-to-sitting, and running.

A complete illustrated scheme presented in an interactive application, with the first step being the selection of a motor skill from the previously listed skills, is available in the official *Benchmarking Locomotion Website* [10].

Once the skill is fully determined and characterized, the following action towards the assessment corresponds to selecting the desired measures to be taken when performing it.

13.4 Performance Indicators

As mentioned before, there are multiple ways to measure motor skill performance. A first and useful way to organize them is by grouping them into two categories defined in Fig. 13.1 that relate to the different levels of performance observations, as suggested by Magill [7]. The first type, the performance outcome indicators, received another name in Pinto-Fernandez et al. [5] and will be the one adopted in this chapter. They label them as Goal-Level variables or measurements. In the second category, the same authors identified two different subgroups that will also be used further on. On one side are the kinematic and kinetic indicators focusing on the limbs, head, or body movements that lead to the observed outcomes. On the other side are the HRI measurements that relate more to the variables that might influence the intrinsic interaction between the user and the robotic device. The PIs that correspond to each of these categories will now be addressed.

13.4.1 Goal-Level Performance Indicators

To indicate the results of performing a motor skill, different variables can be considered. The following are the most commonly used Goal-Level PI in the field of the assessment of robotic devices for gait assistance and rehabilitation:

- **Time indicators**
  This category includes various time-related measurements. One of the preferred metrics for performance evaluation is the minimum time or the maximum speed achieved to correctly complete a task. However, another important indicator under this category is the reaction time (RT), which indicates how long it takes for a person to prepare and initiate a movement. Time indicators are mostly calculated during clinical tests, such as the 10 Meter Walking Test (10MWT), the 6 Minute Walking Test (6MWT), and the Timed Up and Go (TUG) test [5], and are measured in time units (e.g., sec, min).
- **Error indicators**
  Metrics related to errors have a prominent place in human performance research and in everyday living activities (assistance and rehabilitation). Multiple ways of reporting errors are accepted and it is up to the researchers to decide if they correspond to a study of accuracy either spatial, temporal, or both. Error indicators can be in the form of: (i) the amount of error in performing criterion movement, e.g., absolute error (AE), constant error (CE), or variable error (VE), or (ii) the number or percentage of errors [7].
- **Distance**
  The distance covered when performing a motor skill with a device is frequently used as PI. In exoskeletons, the 6MWT is found to be the preferred PI in this category [5].
- **Stability (to external disturbances)**
  Stability can be understood as the ability to maintain equilibrium over the support base during the motor skill execution [4]. The PIs in this category include: maintaining the center of mass (CoM) above the polygon of support (what Fleishman on his list referred to as gross body equilibrium), forefoot and rearfoot loading, length of the motion path, or confidence ellipse area [5].
- **Endurance**
  This PI generally refers to the ability to perform long periods of functioning or multiple cycles of work to test the robot's skills (also in the benchmark proposal). Nevertheless, it can also apply to other robotic devices as it is usually measured by the power development per joint, joint stiffness, and battery usage [5].
- **Repetitions**
  PIs under this category are measured with integer numbers and one of the simplest to recognize. Good examples are the number of successful attempts and the number of trials or repetitions to complete the task.
- **Versatility**
  Versatility is here understood as the ability of the robotic devices to cope with

different motor skills in the same run [5]. It is mainly used in cases where an exoskeleton takes part. This PI can be implemented together with the last category by measuring the number of successful transitions between tasks, or independently, with step width adaptability criteria.

Goal-Level PIs, especially time, error, and distance indicators, are very popular and globally accepted indicators. They are relatively simple and practical to use, making them particularly useful during competitions in the area (Cybathlon [3], for example). However, they can be rather insufficient to validate or quantify the robotic systems' performance [5], as robotics in rehabilitation and assistance are highly conditioned to the subject's performance. Given that these PIs are not very reproducible, other types of PIs are usually needed.

13.4.2 Kinematic and Kinetic Performance Indicators

Addressing the robotic device's performance during the motor skill by measuring the production indicators includes many more parameters to consider than the outcome indicators. To capture the complexity of the action to be performed more closely, they require specific instruments and equipment, as presented in the following sections.

Kinematic and kinetic PIs include many of the most common indicators used to assess robotic devices [5]. They are traditionally associated with biomechanics and refer to descriptors of motion without concern for its cause and force as a cause of motion, respectively [7]. Under this category are the following PIs for the assessment of robotic devices in the field:

- **Spatiotemporal Parameters**
  They correspond to parameters of distance (spatial) and time (temporal) during gait. They are considered standard metrics that can grasp the kinematic performance's main features in basic locomotion tasks [5]. The spatial parameters are related to the step and stride length but can include others like the number of steps. On the other hand, temporal parameters comprise the cadence, walking speed and the complete cycle, and individual phase time.
- **Kinematic indicators**
  As previously stated, kinematic indicators are a description of motion without regard to force or mass. As PIs, they portray the displacement, velocity, and acceleration of the human and robotic joints. This includes: joint trajectories, range of motions (ROMs), speed, and CoM position along the three principal planes of motions (sagittal, frontal, and transverse).
- **Kinetic indicators**
  In kinetic indicators, force is the main parameter to consider in the analysis of joints. Therefore, these PIs are of joints torques, force, power, and work, global forces, and power and ground reaction forces (GRF).

- **Symmetry**
  The symmetry indexes are the percentage of symmetry between the right and left gait cycle regarding their curve of acceleration or pelvic angles. Pelvic angles are the tilt, obliquity, and rotation, according to the plane of motion. As the indexes approach 100, the more symmetry there is along the trial [11].
- **Coordination**
  Coordination PIs come after the previously explained spatiotemporal parameters. For a cyclic movement, like gait, an indicator of coordination between two limb segments is the relative phase. This index calculates the phase angles for each limb segment or limb at a specific point in time and then subtracts one phase angle from the other [7].

The first three PIs presented in this section are very popular in assessing exoskeletons as they can grasp the entire complexity of limb dynamics. However, the kinematic and kinetic indicators are often difficult to compare and replicate as there are no typical standard setups, data labeling, or experimental protocols. Symmetry and coordination, on the other hand, are still poorly used in the evaluation of exoskeletons' performance [5].

13.4.3 Human–Robot Interaction Performance Indicators

The second type of performance production indicators comprises all the measurements that characterize the synergy between the user and the robotic device. Given the nature of this group of indicators, HRI PIs include both quantitative and qualitative variables. The first ones evaluate the user's physical parameters, while the others reveal subjective levels of acceptance of the technology by the user during the interaction. The main PIs in this category are:

- **Metabolic cost**
  Metabolic cost is a way to describe the intensity of an activity or motor skill. Many indicators can be used to that end. The most frequent PIs are: heart rate, blood lactate concentration, oxygen consumption, carbon dioxide production, metabolic power, biological power, work, and calorimetry [5, 12].
- **Muscle activity**
  This type of indicator is the most commonly employed variable for the assessment of HRI. It is generally measured by electromyography (EMG), in which the intention of movement is captured through muscles' electrical activity. EMG recordings are relevant to motor learning and control issues as they can indicate when a muscle begins and ends activation [7] and can be used to quantify the effects of a robot on muscle fatigue.
- **Brain activity**
  Research on the relationship between brain activity and performance has led to rapid brain assessment technology implementation on motor rehabilitation.

Similar to the previous indicators, brain activity is usually measured by electroencephalography (EEG) recordings.

- **Interaction forces**
  This category does not need any extra information other than the fact that it is measured through three PIs: the power delivered to the robot, the interface transmitted forces, and the interaction forces themselves.
- **Comfort**
  Comfort is defined in this document as the user's perception of the HRI. This one corresponds to the qualitative variables previously mentioned and has many ways of being measured. Among the most relevant indicators are pain scales, skin irritation, sore spots, spasticity, clinical questionnaires, and user sense of comfort [5].
- **Ergonomics**
  Ergonomics refers to the design and arrangement of things people use to make the interaction the most efficient and safe possible. The main PIs used in this category are HR relative position, interface displacements, anthropometric database percentiles, and adaptability to different height ranges [5].
- **Safety**
  This indicator assesses the condition of being protected from harm or other non-desirable outcomes. Safety PIs are a mix of both quantitative and qualitative indicators. Quantitative PIs are the number of falls, blood pressure, and heart rate. Qualitative PIs include the skin, spine, and joint status after using the robot, and clinical questionnaires similar to those implemented for comfort.

Some of the most expected performance outcomes and production measurements here are included in the official *Benchmarking Locomotion Website* [10]. They correspond to the second step of selecting the organization of the currently available metrics and protocols to assess bipedal function into a meaningful taxonomy.

Keeping in mind the provided overview of the motor skills and PI, the only unexplored and missing area to fully understand how to assess robotic devices in gait assistance and rehabilitation is the section of the required equipment and sensors.

13.5 Equipment and Sensors

By equipment and sensors, one should understand in this chapter all the set of tools, devices, and kits, assembled to measure and capture the different PIs for the chosen motor skills. Regarding their location, the equipment and sensors can: (i) be mounted or fixed in the testing environment and record from strategic points of the activity or the specific events, or (ii) be wearable, which means that the user wears them during the performance of the motor skill. The first type is considered the gold standard in accuracy for walking kinematics [13], but their main disadvantages are the price and their limitation to indoor use with a very controlled environment [14]. On the contrary, wearable sensors have become popular due to their affordability and flexibility of use, together with shorter donning/doffing times [15].

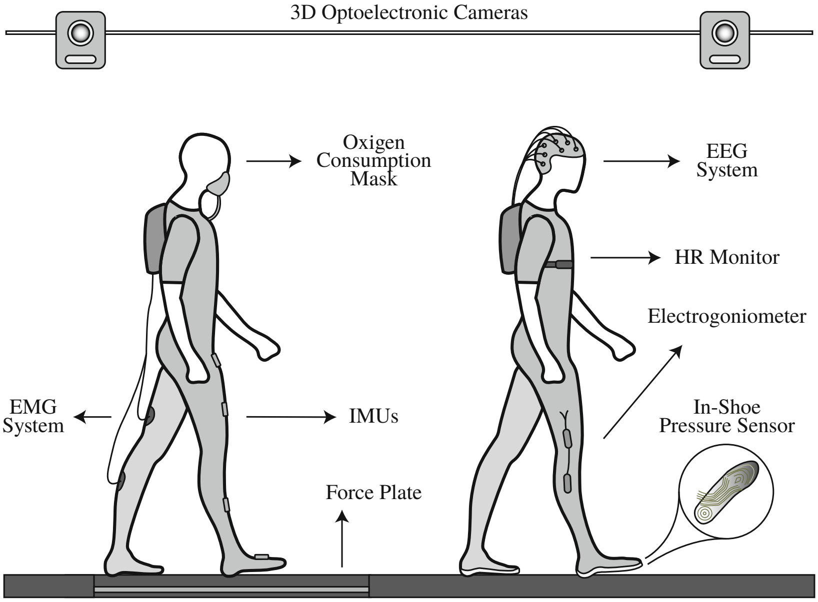

Fig. 13.2 Equipment and sensors used for the assessment of robotic devices in gait assistance and rehabilitation

This section presents a non-exhaustive catalog of the leading equipment and sensors used to assess the motor skills' performance, as mentioned earlier, employing the desired PI. Most of them are depicted in Fig. 13.2. They are grouped in the same categories used to classify the PIs. Given the purpose of the Goal-Level PIs and their intention to measure outcomes, most of the metrics are not complex and with simple equipment like timers, counters, and rulers can be calculated. Therefore, no further details are presented regarding this kind of PI, except possibly for stability, which can be addressed with the equipment of other kinematic and kinetic PIs.

13.5.1 Equipment and Sensors for Kinematic and Kinetic Performance Indicators

The extraction of most kinematic PIs (including spatiotemporal, symmetry, and coordination) was first done with portable sensors called electrogoniometers. Afterward, the measurements evolved to 2D and 3D video systems, which need to be placed in the performance environment, depend on specific laboratory conditions and imply complex protocols and high economic costs. Nowadays, the extraction is moving back to relay on wearable sensors like inertial motion units (IMUs).

13.5.1.1 Electrogoniometers

Electrogoniometers are electromechanical devices that span the joint to be measured by attaching to the proximal and distal limb segments. They measure the joint's angular change by providing an output voltage proportional to the change and assuming that the attachment segments move with the limb segment's midline [16]. The two significant advantages of these devices are ease of use and low cost. However, a significant limitation in using them is that the angles are only acquired in a single motion plane [17].

13.5.1.2 Video Systems

Video systems are based on a computer vision approach, in which the main goal is to extract gait patterns from sequential images [18]. There are both 2D and 3D configurations and it depends on the complexity of the motor skill and the chosen PI, which of them to implement. 2D Systems, as electrogoniometers, can record joint angles in only one plane of motion. 3D Systems, through the inclusion of depth, can extract joint angles in all three planes. The use of active (LED markers that are pulsed sequentially) or passive (lightweight reflective markers) markers is widespread when implementing this kind of system, even though some have worked their way out of the markers. The leading video systems used in the field are:

- **2D Systems**
  The Kinect is the most used exemplar of this technology. First developed by Microsoft, in 2010, collects information from RGB cameras, infrared projectors, and detectors that mapped depth to perform real-time gesture recognition and skeletal body detection, among others. In this sense, a biomechanical model based on rigid segments can be implemented to acquire human motion data [19]. As the human body is modeled, joint angles are acquired while performing a motor skill. As previously mentioned, it can only record angles in one plane of motion, and, in this case, users are not required to wear any markers. Additionally, this equipment is portable (easy to relocate) and low cost. The main drawback is that it is no longer produced as by 2018, Microsoft discontinued all Kinect hardware for video games. Moreover, for those who still can get their hand on them, specific lighting and space conditions (controlled or laboratory conditions) are required.

  Other alternatives to this system include motion tracking software, based on recordings by a 2D camera (and possible reflective markers) to calculate almost all kinematic parameters. *MaxTRAQ 2D* (Innovision Systems, USA) [20] includes tools and analysis of angles, distances, the center of mass, and more.
- **3D Systems**
  3D optoelectronic camera systems for motion capture are often regarded as the gold standard in acquiring biomechanical parameters, given their robustness [21]. They detect light and use it to estimate the 3D position of reflective markers via time-of-flight triangulations. To correctly place markers on the user and allow an optimal estimation many protocols have been developed. The accuracy of these

systems is dependent on the different details of the experimental setup: (a) the location of each of the cameras relative to the others, (b) the distance between the cameras and the markers, (c) the position, number, and type of the markers implemented, and (d) the motion of the markers within the capture volume [22].

Systems of this type are based on fixed cameras, which means they can only acquire data in a restricted area [23]. The number of cameras, their field of view, and the space between them condition the total volume in which the skill can be performed and captured. The most extensive measured range reported, to the authors' knowledge, is 824 m^2, obtained with a Vicon MX13 (UK) measurement system [6]. To capture this range, a total of 24 cameras were required.

Among the major drawbacks of these systems are high costs, lack of portability, constant need for calibration and synchronization, high labor in the organization and processing of trials, and high sensitivity to alterations in setup. By increasing the number of cameras increases the level of all of these items. Further limitations of the system are the necessity of line-of-sight, which means that the data output will be interrupted when the cameras lose sight of the markers [6, 24], and the need for dark areas (indoors), as bright sunlight interferes with the measurements [6].

Important and widely used manufacturers of this technology include: Vicon (UK) [25–27], Motion Analysis (USA) [17, 28, 29], Qualisys (Sweden) [20], and BTS Bioengineering (Italy) [30].

An extensive review of vision-based systems that have been proposed for tracking human motion in the past years can be found in Moeslund et al. [31].

13.5.1.3 Inertial Unit System (IMU)

An inertial measurement unit (IMU) is a sensor composed of the fusion of three other sensors: gyroscopes, accelerometers, and magnetometers. Through this combination of components, the unit can acquire gravitational acceleration and rotational velocity, to estimate the velocity, acceleration, and orientation of the element they are attached to. In a person's lower limbs, they are usually positioned on the waist, thigh, shank, and foot instep [32–34]. To estimate complex PIs, multi-sensor arrangements are widely used to assess a specific task. Several studies used a multi-sensor to estimate and compare the efficacy and precision, analyzing signal patterns of body segments in different locations [35–37]. They are of relatively low cost and provide an alternative to 3D systems as they do not require specific light and space conditions to function properly. Nevertheless, signal processing can be challenging as it involves the fusion of three sensors and the presence of cumulative drift error and the growth of quadratic or cubic error [38], which can distort the measured parameters. There are many commercially available IMUs on the market. From sophisticated modules like Xsens (Netherlands) to simple units from manufacturers as Bosch (Germany) [39].

A complete analysis of the accuracy of the three previously presented systems for the capture and assessment of human motion (aimed but not strictly to sports applications) can be found in the work by van der Kruk and Reijne [40].

13.5.1.4 Ground Reaction Force (GRF) Sensors

To calculate kinetics indicators for each of the joints involved in the motor skill, dedicated software based on inverse kinematics analysis has been developed. The most prominent exponent is *C-motion* (Visual3D, USA) [20, 41, 42]. The basic inputs for this software are: (i) kinematic PI, obtained by any of the motion capture systems shown before, (ii) ground reaction forces (GRF), and (iii) segmental mass distribution models. GRF can be measured with two main types of sensors:

- **Force Platforms or Plates**
  A force platform can be understood as a pair of plates, one over another with force transducers between them at the corners [43]. There are several types of force plates on the market and they are classified either by how many pedestals (single-pedestal or multi-pedestal) or by the type of transducer they employ. The types of transducers commonly found in force platforms are: strain gauge, piezoelectric sensor, capacitance gauge, Hall effect, and piezoresistive sensor, each with the advantages and drawbacks inherent in their nature. For gait analysis, force platforms with three or four pedestals are used to permit forces that migrate across the plate [44]. They are usually synchronized with 3D optoelectronic camera systems to provide a simultaneous analysis of the different PIs [25, 28, 45].
- **Pressure Mapping Systems**
  Pressure mapping systems quantify the interface pressure between two contacting surfaces. They can come in different forms, from walking mats or strip of carpet-like sensors, to a completely wireless thin insole (in-shoe technology). These systems use a larger number of sensors (typically in the hundreds, depending on the size) to capture the pressure distribution and profiles in the foot, and the position and trajectories of the center of pressure (CoP) during stance phases of gait. Nonetheless, they have also been used to measure force profiles during many activities. For example, the F-Scan (TekScan, USA) in-shoe pressure mapping system has been effectively used to measure GRF during able-bodied walking [46, 47], and the Pedar-X mobile (Novel Gmbh, Germany) in-shoe system was used for collecting GRF using a lower limbs exoskeleton [48].

13.5.2 Equipment, Sensors, and Tools for Human–Robot Interaction Performance Indicators

As mentioned in the HRI PI characterization, this type of measurement includes quantitative and qualitative variables. Two big groups of equipment and sensors, which refer to the user's physical parameters, describe the majority of the quantitative HRI indicators. The qualitative PIs are clustered in one independent group in this chapter.

13.5.2.1 Metabolic Cost Systems

Metabolic cost encloses a variety of PIs, as it was presented in Sect. 13.4.3. Authors have measured it in numerous ways and with different types of equipment. Some of the sensors and calculations that best exemplify this are:

(i) Malcom et al. measured the metabolic cost of subjects walking with an exoskeleton through respiratory gas analysis. They analyzed respiratory gasses with a computerized O_2–CO_2 analyzer flow meter (Oxycon Pro, Germany) and estimated metabolic cost with the formula from Brockway [20, 49]. **(ii)** Lee et al. equipped elder exoskeleton users with a facemask connected to a computerized portable cardiopulmonary metabolic system (Cosmed K4B2, Italy), to measure breath-by-breath metabolic costs. They also measured the heart rate via a wireless chest-strap heart rate monitor [29]. **(iii)** Award et al. measured the energy cost of walking in individuals in the chronic phase of stroke recovery using an exosuit. They defined it as mass normalized oxygen consumption per meter ambulated (mlO_2/kg/m) measured with indirect calorimetry (Cosmed K4B2, Italy) and normalized by body weight (kg) and walking speed (m/min) [42]. Finally, **(iv)** Arazpour et al. evaluated the physiological cost index (PCI) of walking (a proxy measure of energy consumption) in a group of subjects with poliomyelitis. They used a Polar Heart Rate monitor (Polar, USA) to evaluate the PCI through a calculation including heart rate at steady-state walking (HRss) and heart rate at rest (HRar) [50].

13.5.2.2 EMG and EEG Systems

Muscle and brain activity and their corresponding subindicators are measured using the electrical signals associated with each human system as mentioned in Sect. 13.4.3. For researchers to achieve non-invasive and painless EMG and EEG recordings, surface electrodes are attached to the skin over muscles (known as surface EMG or sEMG) or a person's scalp. Typically, electrodes are placed on standard locations on the muscles and scalp to measure the voltage fluctuations. In the EEG case, the electrodes are usually contained in an elastic cap in their appropriate locations on the scalp to measure the activity of thousands or millions of neurons immediately beneath them [7]. sEMG systems are widely used to assess muscle activity PI during gait [28, 29, 51].

13.5.2.3 Clinical Scales and Evaluations

This last group comprises all measurements that cannot be captured or characterized with sensors or equipment as the ones explained before. This section intends not to list all the existing tools to assess qualitative PIs, as it would be extensive, but rather to give examples that have been used in the literature.

A detailed description and compilation of more than 500 measures of clinical protocols, scales, indexes, and questionnaires are found in the *Rehabilitation Measures Database Website* of the Shirley Ryan AbilityLab [52]. Additionally, in Chapter 14: *Experiences of Clinicians Using Rehabilitation Robotics*, some of the most used standardized questionnaires to evaluate user's ergonomics, comfort, and safety are presented.

Regarding practical examples of the clinical scales used to assess HRI PI in the field, the following are some of the reported studies:

(i) Visual analog scales (VAS) are used to assess features like user fatigue, pain, and comfort [53]. del-Ama et al. implemented a VAS consisting of a 10 centimeter rectangle. With that scale, the user was asked to rate the pain perception by placing a mark inside the rectangle, rating from no pain at the left edge of the rectangle, to intolerable pain at the right edge of the rectangle [54]. **(ii)** The Ashworth scale (AS) and the Modified Ashworth scale (MAS) are utilized to evaluate spasticity [54, 55], and spasm frequency and severity are quantified using the Penn Spasm Frequency Scale (PSFS) [55]. **(iii)** To evaluate all aspects of patients' health and assess if there has been an improvement or decline in clinical status, the patient's global impression of change (PGIC) is used [55]. Finally, **(iv)** to assess the static balance and fall risk the Berg Balance Scale (BBS) is usually implemented [56].

13.6 Conclusions

The assessment of robotic devices' performance for gait assistance and rehabilitation is a multidisciplinary area that involves the mastering of many different concepts. Recent efforts to benchmark bipedal locomotion have settled the basis to understand the various considerations when classifying a motor skill and measuring its performance. The overview presented hopes to have organized and explained the key components one needs to consider when assessing gait robotic assistive and rehabilitation devices. According to the focus given to the performance, a reasonably detailed description of the implemented measures was achieved through the characterization of the existing PI. Additionally, the inclusion of practical information of their use and application in research intends to favor future studies, where standardized nomenclature, parameters, and benchmarking, in general, are included. Finally, some of the most popular equipment, sensors, and tools used in the literature and commercially available to measure motor performance were described. The knowledge and understanding of all the components presented are fundamental in the process of accurately assessing technology towards better assistance and rehabilitation of patients.

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