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Review

Review and Analysis of Platform-Related Performance of Rehabilitation Lower Limb Exoskeletons

Hossein Karami *, **Stefano Maludrottu, Christian Vassallo, Matteo Laffranchi and Lorenzo De Michieli**

Italian Institute of Technology, Via Morego 30, 16163 Genoa , Italy; stefano.maludrottu@iit.it (S.M.); christian.vassallo@iit.it (C.V.); matteo.laffranchi@iit.it (M.L.); lorenzo.demichieli@iit.it (L.D.M.)
* Correspondence: hossein.karami@iit.it

Abstract: Powered Lower Limb Exoskeletons (PLLE) have attracted much interest due to their potential applications. They provide assistance for persons with disabilities to accomplish activities of daily living (ADL), and more importantly, assist them in achieving their rehabilitation goals. However, there is still uncertainty regarding the quality and benefits that PLLEs can offer to patients. This is due to limited usability and performance of current PLLEs, insufficient clinical use of PLLEs for different patients with high diversity in their disability type and impairment, and also the large gap between the technological state of the art and clinical expectations. In this study, we review and analyse various factors that can improve the effectiveness of PLLEs at yielding better assistance and rehabilitation training for patients with motor impairments. First, we define a set of criteria that characterize the majority of expectations for the rehabilitation and assistance domains and we use them for evaluating PLLEs depending on the context. Then, we include the effects of control strategies and combined approaches which include auxiliary devices such as functional electrical stimulation and smart crutches applied to PLLEs with regard to the criteria we defined.

Keywords: powered lower limb exoskeletons; rehabilitation and assistance; performance criteria; neurological disorders; auxiliary devices; control strategies; effectiveness of PLLE

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1. Introduction

The effectiveness of powered lower limb exoskeletons (PLLEs) in assisting people with locomotion difficulties is pretty new to most of people [1–4]. Indeed, their initial use dates back to the 1960s [5] and their evolution has constantly been progressing over time, even attracting market and clinical interests in recent years. PLLEs are electro-mechanical robotic devices designed to be worn by human end-users which are used to assist them to enhance their lower limb locomotion capabilities.

PLLEs as robotic devices aim to fully or partially replicate human lower limb motor functionalities. Human lower limbs exploit a higher number of degrees of freedom (DoF) and possess a kinematically and dynamically redundant actuation system through muscle-ligament interactions [6,7]. PLLEs, instead, in the vast majority of cases, are under-actuated robotic platforms that incorporate the lower limbs in a parallel arrangement, and adopt rigid mechanical parts (links) and electromechanical motors (joints) located correspondingly to the lower limb joints, for their actuation systems.

Generally, PLLEs can be classified into three main types based on their applications [5,8]. The first type is used for *power augmentation* of healthy people whose target users are mainly soldiers or factory workers to increase their walking distance and durability and workers to help them with carrying and lifting heavy objects in factories. The second type aims at *assisting* subjects with locomotion impairments such as elderly people and individuals who suffer from stroke, spinal cord injury (SCI) or similar neurological diseases and disorders. Lastly, the third type has *therapeutic* applications and is used for training gait patterns and recovering locomotion capabilities of individuals with lower limb disabilities.

Assistive and therapeutic PLLEs, despite structural and design similarities, have different purposes and are often referred to *rehabilitation* lower limb exoskeletons in the literature.

In this review paper, we mainly focus on rehabilitation PLLEs and investigate the *performance* of such *platforms*. Here, by platform, we do not define just the lower limb exoskeleton itself, but we also include control algorithms and strategies adopted to drive PLLEs and, additionally, we comprise auxiliary devices and sensors that can play a complementary but crucial role in the effectiveness of such machines. Although performance assessment of rehabilitation PLLEs is not straightforward and one could evaluate them with any arbitrary metric function due to lack of a ground truth that establishes a reference point of evaluation, we define a series of criteria that we hypothesize, among other important ones, offer more reasonable evaluations of the efficacy of PLLEs from the point of view of rehabilitation expectations and outcomes. In Section 3, we will present these criteria in detail and will address how and to what extent different platform aspects can affect one or more of these criteria.

Several recent review papers have already addressed the effectiveness of PLLEs and their various characteristics. Some of these reviews, clinically evaluated the rehabilitation outcomes of PLLEs in terms of ambulatory spatiotemporal parameters and energy expenditure measurements [9–14]. However, these papers did not evaluate the effect of robotic platform design choices on the rehabilitation outcomes. As the results of robot assisted rehabilitation training suggest, the positive outcomes of PLLEs are still poorly organised and, as a consequence, despite the overall positive results, their benefits and their correlation with the type of patient or the specific technology employed for the training are still unclear.

The lack of works that could systematically and deterministically prove the superiority of PLLEs over conventional therapy methods in gait rehabilitation has raised skepticism and disappointment among researchers and clinicians. In our opinion, this can be mainly because of the following reasons. First, PLLEs, despite their recent considerable advancements, still are emerging technologies at their early development stage, and their current form suffers from many limitations as they are not able to fully provide functional solutions for rehabilitation aims. Second, since PLLEs have not reached a sufficient clinical use yet; thus, robotic rehabilitation is restricted to an insufficient number of patients and/or trials with high heterogeneity. Indeed, diversity in age, weight, gender and underlying pathology type and level, make it difficult to discover subject-specific training protocols that can optimally benefit patients [15].

Third, research and industry groups are rapidly developing new PLLEs and delivering them to the market without considering their use in rehabilitation programs. The gap between engineering designs and clinical expectation is due to the lack of expertise in the vast and distributed rehabilitation science and poor understanding of physiological concepts by engineers who struggle to evaluate the development of PLLEs aligned with rehabilitation outcomes.

Due to the aforementioned reasons, assessment of PLLEs for rehabilitation purposes remains challenging. To overcome this challenge, one desirable but unfeasible approach is to evaluate rehabilitation outcomes of existing PLLEs with respect to a number of platform-related aspects and patient-specific condition variables including a broad range of parameters. Another potential approach, i.e., the one that we propose in this paper, is to study the effects of various platform-related aspects and to exploit reports of rehabilitation trial outcomes to identify the solutions that may improve the efficacy of current existing PLLEs through the performance evaluation criteria that we define in Section 3. In other words, in this work we explore various aspects of PLLEs to discover the most effective design paradigms and how to exploit them for rehabilitation purposes.

Many other review papers investigated PLLEs [16–24], mainly focusing on their mechanical structure, types, design, and clinical applications. A smaller number of reviews, explored control algorithms and strategies employed to drive PLLEs [25–28]. Alternative approaches such as the CYBATHLON competition [29], could provide a benchmark to compare the capability of exoskeletons in the accomplishment of daily life problems through competitions. However, metrics employed to define efficacy, such as the successful execution of a fixed set of tasks in a given time, are not sufficient to appropriately address the performance of exoskeletons [30]. Moreover, the skill of users can substantially influence the results. A more relevant approach in assessing performance of lower limb wearable devices was proposed in the EUROBENCH project [31]. They attempt to introduce standard benchmarks and appropriate performance indicators to help developers and engineers to select an optimal solution based on their needs. However, this approach mainly focuses on performance evaluation at an abstract level where the effect of platform-related solutions are not considered in evaluation process.

The remainder of this paper is organised as follows: Section 2, describes the inclusion and exclusion methods we adopted to select papers for both analysis and review parts. In Section 3, we introduce our performance evaluation criteria and study important parameters that can affect them. In Section 4, we present platform-related aspects in detail and investigate how they can promote different criteria and overall performance of the PLLEs, and Sections 5 and 6 discuss and conclude this paper.

2. Search Methodology and Classification Method

The main goal of this paper is to gather all relevant publications presented in the literature to form a review and analysis over vast and distributed parameters that increase the effectiveness of PLLEs for patients with mobility problems. We focus on different influential factors and evaluate their corresponding effects on the criteria that we define in Section 3. We selected a number of topics to search as follows: (i) neurological disorders and their adverse effects on patients, (ii) clinical reports on outcomes of rehabilitation programs, (iii) works focused on the evaluation and benchmarking PLLEs, (iv) design and structure of existing PLLEs, (v) control strategies, and (vi) auxiliary devices. We found the majority of the papers with repeated queries for all the indicated topics on *Google scholar* and *Scopus* websites. Following the flowchart depicted in Figure 1, we attempted to include more sources by adding highly relevant papers cited in this step, and exclude the irrelevant papers while screening them by title or abstract. We employed a two-layer inclusion and exclusion approach, where the first layer excludes publications not meeting general requirements with the second layer excluding the remaining papers when they did not meet requirement of each specific topic technically.

The general inclusion approach comprises high-quality publications written in English, peer-reviewed conference or journal papers that study overground PLLEs. Works focusing on treadmill-based PLLEs, upper limb exoskeletons and prosthetic devices are immediately excluded. We imposed specific inclusion criteria for each topic such as neurological disorders that affect lower limbs. Publications on clinical reports of rehabilitation should address the indicated disorders and adopt PLLEs for rehabilitation. Papers regarding evaluation and benchmarking should focus on wearable robots and consider physical interactions with the user and the environment. The selected PLLEs in this paper are commercial products or are actively being used as research devices. Publications on control strategies apply the control algorithms on PLLEs and are published after 2016, as we observed that since that year, a huge number of publications directly target rehabilitation PLLEs. Papers with the focus on augmented devices include devices with a proper PLLE.

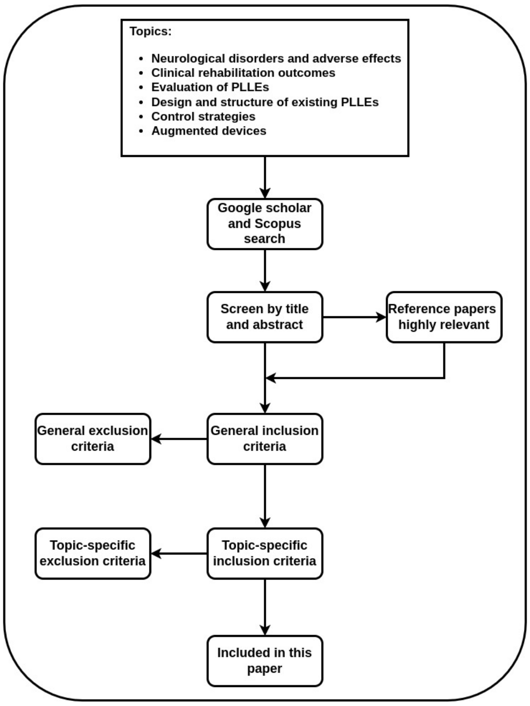


Figure 1. Flowchart representing inclusion and exclusion criteria we adopted for paper selection.

3. Performance Evaluation Criteria

In this section we discuss the evaluation of PLLEs, introducing the existing methods and we exploit them to support our proposed criteria that we use to evaluate PLLE platforms. We justify our approach in detail, explore the criteria we introduce, and identify underlying influential parameters for our eventual analysis. Furthermore, we define the target population of rehabilitation programs and highlight the deficits and impairments that should be addressed.

3.1. Criteria Selection

Assessing the emerging rehabilitation technologies in PLLEs is challenging due to the absence of the defined standard benchmarks for evaluation. The rapid development and delivery of PLLEs by research and industry groups necessitate the development of evaluation and benchmarking tools [32]. Consequently, the authors of [33] introduced a method for assessing and benchmarking for wearable robotic devices, which can be adopted for rehabilitation PLLEs assessment as well, since PLLEs belong to the same family and share many similarities with them in their structure, design and the interaction they have with the human body. They proposed to consider two important perspectives for evaluating these devices: (1) how these devices affect motor functions of the subjects, and (2) the interaction quality between patient and the device, as shown in Figure 2. As *functional* evaluation considers stability, efficiency, kinematics and dynamics of the patient and exoskeleton as a whole, the *interaction* evaluation includes physical and cognitive aspects between human and exoskeleton and also takes into account safety issues for the patient.

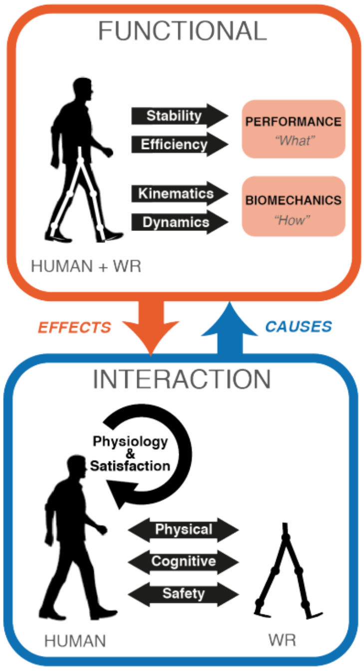


Figure 2. Wearable robot (WR) evaluation perspectives to be considered as proposed by [33].

In functional evaluation, performance is defined as the level of accomplishment of a certain task such as walking speed, or body displacement. It can be further divided it into two sub-modules, namely, *stability* as an index to assess performance in the presence of disturbances and *efficiency* as an index to measure cost of transportation and energy consumption. The functional evaluation related to biomechanical aspects considers how PLLEs can compensate and improve walking patterns. This can be achieved through either the study of kinematic models where various aspects of the motion such as center of mass (CoM), center of pressure (CoP) or inter-limb coordination are important or focusing on dynamic parameters, where inertia, ground/contacts reaction forces and gravity are considered.

In interaction evaluation, physical human–robot interaction becomes of high importance and it measures how the interaction is exploited to assist during walking, not to limit the user movements and its capability in ensuring comfort of the user. Instead, cognitive interaction metric measures the gap between human wishes and robot actions.

Despite such a precise selection of evaluation perspectives and aspects, the presented method considers all the wearable robots and does not address *rehabilitation* PLLEs specifically. Consequently, functional and interaction aspects are defined as abstract concepts and require accurate and specific implementations to match to rehabilitation PLLEs and their expected outcomes. Furthermore, in many cases, evaluation of performance aspects individually does not lead to meaningful outcomes, while a combined set of aspects might give a better perspective.

To have a clear evaluation of rehabilitation PLLEs which considers the evaluation perspectives described above, we identify a series of performance evaluation criteria as follows:

- Gait rehabilitation (GAR);
- Balance maintenance (BAM);
- Decision making (DEM);
- Locomotion modes (LOM);
- Safety, ergonomy and clinical use (SEC).

Each of these criteria incorporates one or more of the mentioned functional and interaction evaluation perspectives as shown in Table 1. Note that these criteria are not mutually independent and they may overlap in some aspects, but each of them potentially considers important functionalities that PLLEs can deliver. They have been selected so that their overall contribution covers a wide and representative range of expected outcomes of both therapeutic and assistance applications. Later in this section, we will discuss in detail the importance of these criteria and potential factors that can influence them.

Table 1. The one-to-some mappings between the evaluation perspectives presented in [33], and our performance evaluation criteria for PLLEs.

Perspective, Criteria	GAR	BAM	DEM	LOM	SEC
Stability				✓	✓
Efficiency					✓
Kinematics	✓	✓		✓	
Dynamics	✓	✓		✓	✓
Physical interaction	✓	✓			✓
Cognitive interaction	✓		✓		
Safety		✓			✓

Table 1 describes the relationship and mappings between our described criteria and the ones defined in [33]. For instance, GAR criteria involves kinematics, dynamics, cognitive and physical interaction aspects. This is because different parameters, such as gait pattern, the quality of interaction between patient and the PLLE, and cognitive encouragement of patient have direct and indirect influence on improving GAR. Later in this section, we elaborate all the parameters that have heavy impacts on these mappings for all the mentioned criteria.

Robot-Assisted Rehabilitation and Target Population

Robot-assisted rehabilitation provides additional benefits compared to conventional rehabilitation methods. This is a consequence of many different factors that contribute at offering repeatable and intensive movement patterns. These are: robots are able to be highly precise, to convey a wide range of motions and forces, to sustain intensive assistance and training for a long period of time, to offer a standardized environment, to increase the dose and intensity of the therapy, and in some ways to assess the progress of recovery in terms of kinematics and kinetics.

PLLEs are expected to respond to a wide spectrum of demands to achieve efficient results within rehabilitation programs. Their primary objectives are to: (i) adaptively assist patients with various pathology types and levels in their daily living activities, (ii) provide modulated therapeutic solutions for recovery and training programs, (iii) reduce the physical burden of physiotherapists in rehabilitation activities, and (iv) continuously monitor performance and improvement of patients to adapt themselves accordingly to time-varying circumstances of patients.

Target population for PLLE-based rehabilitation are patients that have complete or severe impairment of lower limb mobility due to, e.g., neurological disorders with central nervous system (CNS) impairments, that mainly result from stroke, spinal cord injury (SCI), severe brain injury (SBI), multiple sclerosis (MS) and Parkinson’s disease.

To better understand how rehabilitation can effectively impact gait recovery, we need first to define what adverse effects different neurological disorders can cause on gait. Patients with SCI, SBI and MS have many deficits in common, as these disorders stem from CNS impairment. In many cases, findings made in rehabilitation of a CNS lesion such as stroke are valid for other lesions such as SCI and can hence be equivalent [34]. However, described neural disorders are caused due to different reasons and they manifest the impairments in various forms and levels. Despite the type and level of symptoms that patients may develop following various incidents, we need to consider that their mobility is compromised.

Stroke is the most common neural disorder with the largest patient size among all patients with CNS lesion. Road vehicle accidents [35] are common causes of SCI. SCI, also, depending on completeness and location of injury, leaves patients with different levels of impairment and it mainly manifests in the form of paraparesis and in severe cases quadriparesis.

The aforementioned target patients, despite their varying type and level of mobility impairments, share some common biological deficits. They suffer from reduced or null force and torque outputs of the muscles in their paretic limb, although reports stated that unaffected limbs also suffer to some degree from this deficit [36–39]. Furthermore, these patients have compromised motor control synergy, whereby synergy refers to the template of complex neuromechanical outputs based on a modular combination of basic activation patterns of muscle groups shifted in time and amplitude [40]. Abnormal synergies reduce the ability of patients to control certain muscle groups independently from others and lead to activation of undesired secondary torques (torques created in adjacent joints while attempting to exert torque in a certain joint) [41,42].

3.2. Selected Performance Criteria

In this part, we describe our selected performance criteria in detail. We also discuss the importance of them technically. Various parameters that can leave substantial impacts for improvement of these performance criteria are considered and we discuss how these parameters can be implemented employing PLLEs.

3.2.1. Gait Rehabilitation (GAR)

Gait rehabilitation or recovery is the primary objective of neurorehabilitation training [43] as neurological disorders leave individuals with gait abnormalities such as reduced walking speed, uncoordinated inter-limb walking pattern, asymmetric step length, muscle weakness, compromised balance and force reduction [44]. However, regaining all described skills and functionalities is typically possible and at the same time complete recovery requires extensive time and effort. Therefore, success in robot-assisted rehabilitation is defined by achieving the primary outcome, that is, regaining the ability to walk independently, and measuring secondary outcomes such as walking speed and walking capacity (metres walked in a certain time) [14,45]. The spectrum of human locomotion phases characterised by biomechanical events can be found in Figure 3.

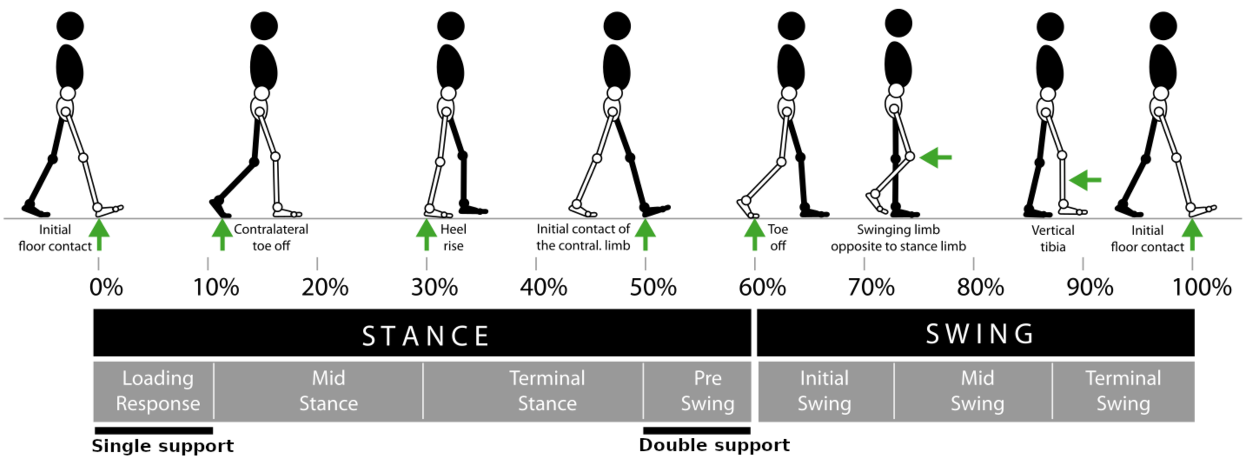


Figure 3. Spectrum of human locomotion phases characterised by bio mechanical events. Overall gait is divided into stance and swing phases. Each phase comprises some sub-phase segments representing bio mechanical events [46].

GAR training should aim at overcoming not only primary complications of the incident but also to prevent deconditioning of patients due to effects of secondary complications. Early training plays a crucial role, specifically for stroke survivors, as the patients in the first six months after stroke have the maximum likelihood of recovery [47–49].

Generally, GAR is a process which involves motor learning that can be promoted through both recovery and compensation mechanisms. Recovery is referred as employment of undamaged regions of the brain to activate the same muscles used before the injury, while compensation, in contrast, is the recruitment of alternative muscles to accomplish the same task [50]. There are several factors that have proven to influence the gait rehabilitation program effectiveness. *Intensity of activity* is a fundamental factor for the improvement of the performances in motor learning [51]. Although intensive activity in very simple forms, i.e., repeating the same activities over and over again, might be considered the most effective approach, it can be misleading in terms of providing temporary improvements [52]; therefore, it can not be considered the sole factor contributing to optimal gait rehabilitation. *Variability* of activities, i.e., performing various activities in a random fashion, shifting the order of activities and changing the frequency of the rest times among them, leads to the achievement of a more effective performance in motor learning rather than performing simple repetitive activities [53,54]. This can be associated with the fact that, in random activities, each action is considered a problem to be solved and it will lead to skill learning, whereas simple activities promote the memorizing of motions and forces in time sequences and replicating them later [50]. Furthermore, therapy limited to simple tasks and targeting specific muscles may improve muscle motion and strength; however often it fails to translate into motor learning and function improvement [55–57]. Another important factor in recovery and motor learning is *active physical and cognitive engagement* of patients in training [34]. There are a number of ways to actively engage the patients during training. Adaptive assistance, for instance, cooperatively engages the patient and introduces gait variations that can lead to retraining the neural network in the spinal cord [58]. Cognitive challenges also can lead to actively engage patients to simultaneously improve motor and cognitive deficits [59]. Another approach to challenge patients while preventing cognitive stress and frustration is to adaptively change the difficulty of the training according to patients capabilities [60], as it has been shown that matching the complexity of tasks to the skill level of the patients leads to improvement in learning efficacy [61].

3.2.2. Balance Maintenance (BAM)

Balance dysfunction in patients with CNS lesions typically results in muscle weakness and uncoordinated gait patterns. Maintaining good levels of balance and stability over the rehabilitation session is one important limitation in current PLLEs and patients often struggle to keep their balance after standing up despite using crutches or while receiving physical support from a therapist. The balance mechanism revolves around the interaction of ground reaction forces (GRFs) applied to the human body and the kinematic configuration of body segments. The sum of GRF vectors acting on various parts of the human body pass through the CoP. Similarly, the configuration of body segments with different masses defines a point of application referred to as CoM. The Euclidean distance between the CoP and CoM is the determinant factor for balance and stability, thus balance assistance deals with both kinematics and kinetics of PLLE and the wearer as a whole. As shown in Figure 4 (left), whenever CoP resultant of GRF passes through the CoM, the net rate of angular momentum becomes zero and stability is guaranteed, while, in Figure 4 (right), the notable Euclidean distance between the GRF vector passing from the CoP to CoM creates a non-zero rate of angular momentum causing a fall situation. BAM can be defined as a sustainable locomotion pattern without risks of falling or injury. Balance allows for safe return to a statically stable configuration [62] and maintaining the upright posture of a human wearing a PLLE.

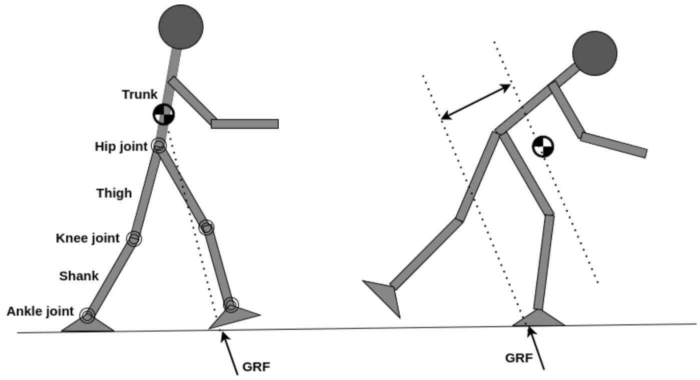


Figure 4. (**left**) Vector of GRF (summation of ground normal reaction and friction forces) passes through CoM and rate of angular momentum is zero and balance is maintained. (**right**) GRF vector is creating a clock-wise rate of angular momentum and causing an excessive forward lean and enhancing fall danger.

Humans implicitly adopt *ankle strategy*, or *hip strategy*, or *foot placement*, or a modular combination of them [63], to reach a plateau state of balance while walking or standing. Ankle strategy regulates CoP positioning by means of ankle motions, and hip strategy by attempts to adjust angular momentum of body segments by means of hip flexion and extensions in order to reach a static balance. Ankle and hip strategies are more prevalent for the stance phase of locomotion, while foot placement adjustment is predominantly employed for dynamic balance while walking [64]. In static stability, projection of CoM in the transverse plane is restricted to remain inside the support polygon, that is, the contact area of the stance foot with the ground in case of single support and the polygon area that bounds both feet in the transverse plane in case of double support. Note that in the case of using a cane or crutches, the support polygon is formed by the bound area of feet and cane/crutches. Instead, in dynamic stability, CoM is able to freely move and exit the support polygon and provide faster gaits [65].

As dynamical balance of locomotion heavily relies on step length in the sagittal plane, step width in the frontal plane also plays a crucial role in maintaining balance [66]. Hip flexion and extension are required for balancing in the sagittal plane and hip abduction and adduction guarantee stability in the frontal plane. Figure 5 depicts human body planes in anatomical positions. Humans do not have direct control over GRF and CoP adjustment, and modulate it through dynamic coupling [67]; thus, it seems the optimal solution to maintain balance in PLLEs is to implement hip strategies in stance phase and adjust foot placements in swing phase.

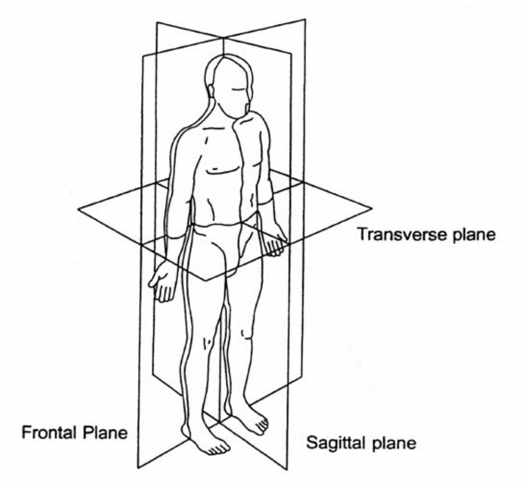


Figure 5. The reference planes of the human body in the standard anatomical position [68].

Apart from the effective role of lower limb segments in BAM, upper limb segments such as trunk and arms are also important in both static and dynamic balance maintenance and recovery [69]. Humans exploit arm and trunk motions to adjust to or cancel angular momentum resultant from GRF in both the sagittal and frontal planes to keep a stable locomotion or to recover stability in the presence of perturbations. Note that, in PLLEs, the trunk and arms are not actuated and in many cases the trunk is spatially restricted and arms do not follow physiological motions to adjust the overall angular momentum of the body as crutches or walker are employed to guarantee stability. Nevertheless, a feedback from upper limb configurations and motions can be helpful with stability strategies.

BAM, balance recovery and fall prevention are not only meant to guarantee safety; in theory, appropriate designs of PLLEs and/or control strategies would free patients from dependence on the support of crutches or walkers, since walking the aid of crutches or walkers induces asymmetric and discrete walking patterns and uncoordinated lower and upper limb motions. This may lead to slow or inefficient rehabilitation programs, as training follows non-physiological patterns. Moreover, recovered patients may adapt to non-physiological lower and upper limb synergies with added asymmetries, leading to secondary complications as discussed in Section 3.2.1.

As discussed above, balance maintenance is a complex issue and both PLLE structure and control strategies play critical roles in determining it. However, we need to consider a number of factors once aiming to include balance and fall recovery solutions into a PLLE. Firstly, the design of PLLEs should follow human anatomy and be able to mimic human body and motions as precisely as possible to avoid introducing abnormalities. Secondly, balance maintenance solutions should not override normal human motions and do not act as opposing forces to muscles unless in severe balance challenges [70]. Third, following the definition of balance, as stated previously, balance solutions should be actively monitoring locomotion to predict falling hazard, and must be triggered only if danger of fall is detected.

3.2.3. Locomotion Modes (LOM)

Activities of daily living (ADL) are not limited to walking on level grounds and they incorporate numerous modes from ascending and descending stairs and slopes, to walking on unstructured terrain. One of the main drawbacks of current PLLEs that prevents them from being widely used both for assistive and therapeutic applications in daily activities is their inefficiency in autonomous recognition of LOMs, immediate adaptation and smooth switching among them. Current solutions employ manual switching of locomotion modes triggered by the user or an assistant. Although manual switching guarantees reliability and robustness, it poses discontinuity in locomotion and can implement only few locomotion switching schemes with prior knowledge of locomotion parameters. Moreover, manual switching to some degrees decreases the independence of the user in mobility. Switching LOM entails a number of considerations as kinematic and kinetic aspects may change drastically and need prompt actions to be taken by the PLLE.

It is noteworthy to indicate that errors in mode recognition would lead to incorrect mode changes and result in actions opposed to volitional control of the user, increasing the risk of harm [71].

The ability of switching from one locomotion mode to another, enhances balance maintenance and recovery, and ensures safety. Moreover, smooth transition among modes promotes natural and continuous gait patterns in patients.

3.2.4. Decision Making (DEM)

DEM is an important criteria for the effectiveness of the PLLEs. By DEM, we refer to the capability of the PLLEs in managing between the decisions and intentions coming from the patient and the actuation control of the PLLE. In other words, DEM evaluates how well the priority between human decisions and the exoskeleton actuation, and ultimately, the safety in the double-agent paradigm context, is addressed. We emphasize that the decisions are not related only to low-level gait pattern parameters; they also include high-level LOM functionalities.

PLLEs must ensure an effective physical and engaging cognitive interaction with the patients, as it is essential for both assistive and therapeutic applications. Solutions which focus on realising effective DEM promote patient engagement. They also cognitively encourage and motivate patients to take the lead in their activities and prevent them from slacking. Moreover, including decisions of patients in locomotion considers them as active human counterpart subjects rather than passive objects.

PLLEs can adapt to wearer decisions both proactively and reactively. Proactive adaptation refers to the recruitment of signals acquired from CNS or other musculoskeletal segments and identification of intents prior to muscle motions, and accordingly actuate the PLLE to fulfill human intentions, whereas reactive adaptation is functionally triggered by measuring signals such as force and position that arise from physical interaction between human and PLLE. In contrast to reactive adaptation that is formed on the basis of physical interaction, proactive adaptation is resultant from cognitive interactions.

The inclusion of decisions and intentions of patients can be obtained within volitional-based rehabilitation strategies such as *assistance-as-needed* [72,73], *human-in-the-loop* [74,75] and *user-centered* concepts [76], where the level of assistance is regulated with regard to detected intentions and the evolution of the therapy [77].

The aforementioned assistive strategies require precise intent recognition and analysis that takes into account the specific impairment of the patient, since different pathologies require specific interventions in assisting them.

Biological signals received from injured limbs are different from those of healthy limbs and in some cases are absent. Hence, in many cases they may provide misleading information of patient intents. Therefore, a PLLE might need to implement alternative approaches exploiting unaffected limbs [78–81], walking supports such as a cane, crutches or a walker, since they take part in the coordination of the gait and their movements represent upper limb motions and contribute to the whole synergy of locomotion [82].

The main factors that would help patients to gain control over the locomotion activities are gait initiation, gait termination, walking at a preferred speed, ability to switch between gait activities such as sitting down, standing up, ascending and descending stairs and slopes. To this aim, recognition of human decisions in locomotion can be divided into two types: gait phase recognition and gait activity recognition [83]. Human gait is formed by two main phases of stance and swing as shown in Figure 3. Generally, gait can be divided into seven discrete and ordered inter-state transitions, namely, loading response, mid stance, terminal stance and pre swing in the stance phase, and initial swing, mid swing and terminal swing in the swing phase. Since recognition of numerous state transitions is very complex and prone to error, in some cases, a more simple division, where only single support, double support and swing phases are detected, might lead to satisfactory results. Among all the gait-related DEM activities, gait initiation and termination are of higher importance, as they potentially promote cognitive capability and provide a positive feeling for patients on being independent in controlling their locomotion. Gait initiation is the transition from the upright standing position to a toe-off event and is characterized by anticipatory postural adjustments where CoP is shifted [84], whereas gait termination is the transition from a steady-state gait to the upright standing; the person in the final step increases braking forces of the lead foot and reduces push-off of trailing foot [85], preparing for a complete stop. Recognition of gait initiation and termination, due to their complex biomechanical transition and the independent volition of the patient that can occur at any time, is a challenging task, whereas detecting gate phases between initiation and termination, due to cyclic nature of the gait, remains less challenging.

Similarly, gait activity recognition can be defined as a smooth transition from one locomotion mode to another where the termination of the former and the initiation of the latter are neglected to provide continuous and monotonic gait motion. Gait activity change detection, for analogous reasons of gait initiation and termination detection, is a challenging task and demands accurate detection and processing.

3.2.5. Safety, Ergonomics and Clinical Use (SEC)

Safety is a crucial aspect in the evaluation of PLLEs. Despite their indubious advantage on supporting patients, PLLEs can potentially cause severe adverse events. Safety requirements should be considered from the early development phase of design and throughout its entire lifetime. Safety can be defined as an abstract representation of the ability of PLLEs in reducing a specific risk or dealing with a specific hazard [86]. Adverse effects often vary from discomfort, cardiovascular events, pain and injuries to bone fractures [87,88]. Adverse events do not only compromise the health of patients, but they also prevent patients from receiving continuous training and assistance from PLLEs. Reports in [14] indicate that a notable number of dropouts in clinical trials for gait training were due to adverse events related to pain and skin breakdown [88]. The main sources of concern regarding safety arise from the PLLE itself, the prolonged interaction of vulnerable subjects with PLLEs and their interaction as a whole with the environment. Those risks might be relevant even in controlled environments such as clinics. PLLEs are required to be compliant to the human body to avoid injuries and, at the same time, they should be stiff enough to convey forces to the human musculoskeletal system through contact points such as straps and foot plates to achieve the desired effects [44,86].

Although all PLLEs are required to acquire safety and conformity approvals from representative authorities before being delivered to the market, several adverse events and safety issues have been reported in [89]. This study, in particular, reported adverse events and identified risks associated with a series of PLLEs which had received necessary approvals as commercial medical devices. Non-ergonomic design and device malfunctioning seem to be the major reasons for the incidents.

Fully ergonomic design of PLLEs is in theory difficult and in practice impossible, since PLLEs are designed to provide the minimal functional representation of a human lower body. A complete and human-like design of PLLEs with existing technologies adds high complexity in design, compromises technical performance and deviates PLLEs from their final objectives. However, monitoring and controlling ergonomy-related issues such as misalignment of PLLEs to lower body and non-physiological joint ranges can substantially reduce the associated risks.

Misalignment of PLLEs with the human lower body is related to non concentric alignment of PLLE actuators with human joint axes that can be the result of either wrong dimension of PLLE segments, or poor adherence of straps or cuffs with the patient during locomotion. This misalignment negatively impacts the physical interaction with the patient and introduces hazards to the human body [90]. To alleviate this concern, some works proposed polycentric knee joints [91] for improving kinematic compatibility with human knee, especially at a high degree of knee flexion. Another likely hazard is exceeding human joint limits such as moving the limb beyond anatomical joint range of motion (RoM), moving at high velocity and acceleration and introducing jerky motions, especially at the beginning of the gait. These limits are subjective and specific considerations need to be taken into account for each patient at different recovery levels.

Another important factor for rehabilitation in PLLEs is their applicability in clinical use. This can be achieved by considering several factors while designing PLLEs. Clinicians prefer to operate with easy-to-handle devices, where they can easily take control of the device and configure it for their clinical aims. Patients with different physical conditions demand a modular PLLE, easily adjustable to their physical characteristics. They also differ in their neurological disorder, and this requires configurable levels of assistance and modes of use, which should be readily accessible for clinicians. Another possible approach for improving SEC is to include human-centred design methods from the initial phases of design and development of PLLEs. However, these kind of methods are usually complicated and entail ethical, methodological and financial challenges [92].

Durability of batteries and possibility for easy and fast battery recharging and replacement are also important to ensure clinical use. Lower weight of the PLLE also increases portability and overall performance, since it is easier for clinicians to guide patients with severe balance problems. Other design choices, such as compact design of PLLEs, employing compact motors, avoiding exposed cables and proper placement of batteries and computer systems [93], are also fundamental for clinical use.

4. Platform-Related Apparatus

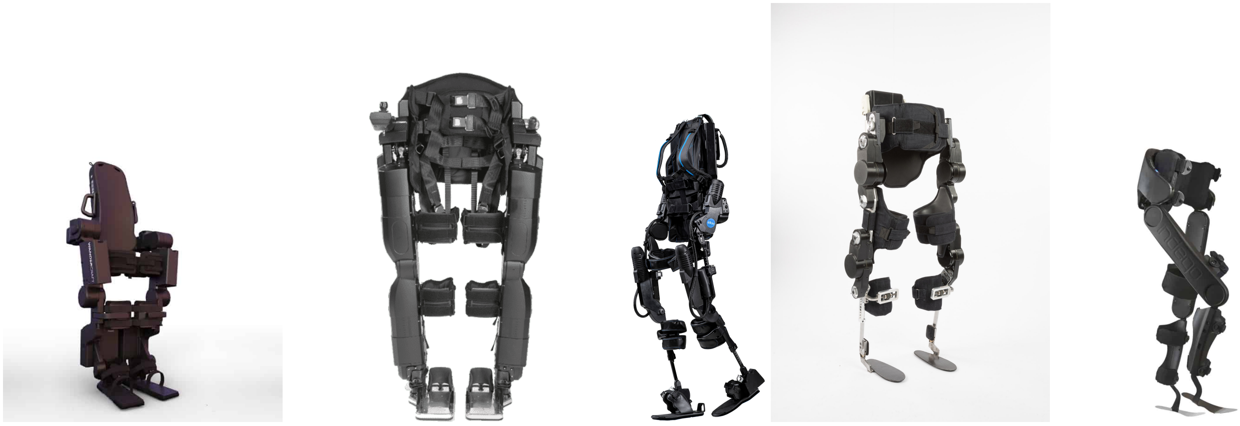
In this section, we study the main components which form the platform, namely, exoskeletons, control strategies and augmented devices. For exoskeletons, we investigate different types of PLLEs, their structure and components. We review current PLLE technologies and compare them with the best solutions using our proposed performance evaluation criteria. Similarly, for control strategies, we present a review of control strategies adopted for rehabilitation PLLEs and analyse how these approaches can best provide rehabilitative and assistive solutions considering our criteria. Finally, we explore possible accessory devices that can increase the performance, compensate for the limits of PLLEs, or provide other functionalities for the control of the devices. We investigate to what extent they are used and analyse their contribution in extending the performance of PLLEs.

4.1. Lower limb Exoskeletons

Rehabilitation PLLEs are designed and manufactured to partially or completely compensate for lower limbs' loss of motor function, as shown in Figure 6. Those which partially compensate the patient strength provide support only for one or few joints or a single limb. In contrast, complete ones cover both legs and provide at least support for locomotion in the sagittal and/or frontal plane. Some examples of complete PLLEs are shown in Figure 6f–g. In this review paper we mainly focus on complete PLLEs.

(**a**) (**b**) (**c**) (**d**) (**e**)

Figure 6. *Cont.*



(**f**) (**g**) (**h**) (**i**) (**j**)

Figure 6. Some examples of partial PLLEs: (**a**) Honda Walking Assist, with two active hip joints [94], (**b**) C-Brace orthotic device [95], (**c**) Hal single-leg exoskeleton with actuated hip and knee joints [79], (**d**) AlterG Bionic Leg with actuated knee joint [96] and (**e**) MAK, actuated knee [97]. Some examples of complete PLLEs: (**f**) Atalante of Wandercraft with 12 DoF [94], (**g**) REX PLLE with ten actuated joints [98], (**h**) Ekso GT exoskeleton with four actuated joints [99], (**i**) TWIN PLLE with four actuated joints [100] and (**j**) Indego PLLE with four actuated joints [101].

To achieve safe and efficient physical interaction between a PLLE and the wearer, PLLEs are required to give assistance following the anthropomorphic structure of the human body and to mimic biological lower limb functionalities. Each lower limb is composed of three main joints: One hip joint with three DoFs provides flexion and extension, abduction and adduction, and internal and external rotations, respectively, in sagittal, frontal and transverse anatomical planes. One single DoF joint actuates knee for both flexion and extension in sagittal plane. Similar to the hip, one joint with three DoFs applies rotations of the ankle in all three planes. Therefore, to achieve fully anthropomorphic kinematics, PLLEs should possess seven DoFs for each leg. Anthropomorphic design has a direct impact on BAM and SEC as humans maintain their static and dynamic balance by using all the joints and the corresponding muscles. We can hypothesize that anthropomorphic design can also affect the quality of GAR, since it enables the training of all the major and interconnected muscles. However, among developed PLLEs, a small number of them possess seven or more DoFs for each leg. Berkeley lower extremity exoskeleton (BLEEX) [102] was the first PLLE to aim for fully anthropomorphic design of PLLEs. Atalante and REX to date, are the only rehabilitation PLLEs that follow an anthropomorphic design with complete DoFs for each leg, although not all of their DoFs are actuated. The majority of rehabilitation PLLEs are underactuated, typically providing support only in the sagittal plane with active hip and knee without ankle actuators. Obviously enough, technological barriers, excessive weight, cost and size, geometrical and design limitations are the main factors preventing optimal anthropomorphic design of current PLLEs. A list of commercially available or common PLLEs used in research are shown in Figure 7a. As it is shown, all of the listed PLLEs support hip and knee flexion/extension (FE) actuation. Only few of them support ankle actuation and in the majority of designs, ankles are passive joints. Considerations about the weight and complexities of the system, design limitations and small range of motion (RoM) of some biological DoFs are the main reasons to alternate active actuators with passive joints. This implies that research groups and industries over the years have reached a consensus on commonalities of the design of PLLEs. However, the ankle joint, despite having a low range of motion, has a predominant role in the locomotion and its active presence provides immediate changes to gait kinematics [103]. It is the first joint to meet GRFs applied to the human foot and therefore its active presence becomes necessary in different phases of the gait. In the toe-off phase, it can act as a thrust force in pushing the human to move forward. In the swing phase, it applies enough force to damp the released energy of the toe-off phase to guarantee a stable and level foot positioning, and in the heel-strike phase, it absorbs the energy resulting from the impact with the ground and prevents the disturbance to knee and hip joints [104]. Information of RoM of the joints of PLLEs in Figure 7a demonstrate that there is considerable deviation between the RoM of joints and those of human walking [18]. This incompatibility is mainly corrected at the software level and by means of control strategies. However, exceeding the normal RoM of human joints, especially for patients with stiff muscles and fragile joints, imposes a high risk of danger and has negative influence on SEC.

Another fundamental requirement for PLLE design is their mechanical compliance. PLLEs, due to their tight physical interaction with the lower limbs, are required to mechanically conform to lower limbs by compliantly adapting to the configuration of biological legs to avoid risks and ensure SEC. Moreover, compliant legs are essential to achieve basic walking mechanics [105], since stiff legs are not able to reproduce human-like motions. In humans, actuation and compliance mechanisms are possible by means of an integrated complex of muscles and tendons. Compliance is the result of the visco-elastic properties of muscles and series-elastic behavior of tendons. The activation and contraction velocity of muscles also play a role in the stiffness of the joints [46]. However, to implement human-like actuation and compliance mechanisms, recent works have inclined toward using elastic elements embedded within actuators. Although elastic elements in robotic systems in recent years have become prevalent and are widely used even in prosthetic systems, they are rarely adopted in the actuation of complete PLLEs as shown in Figure 7b.

Elastic elements can mainly be categorized into elements with fixed or variable stiffness, or in their arrangement form with the actuators, in series or in parallel. Each form of these arrangements has some advantages for PLLEs. Variable stiffness actuation (VSA) has been developed to replicate the ability of mammals in regulating joint stiffness. However, practical implementation of VSAs within PLLEs is difficult, given the typically cumbersome and complex nature of these devices. Alternatively, series-elastic actuation (SEA) or parallel elastic actuation (PEA), with fixed stiffness, provide an acceptable level of compliance for the actuation of PLLEs. A complete review on the use of compliant actuation in lower limb exoskeletons is addressed in [19]. Obviously enough, compliant behaviour of the mechanical structure of PLLEs and the corresponding actuation system, as it promotes human-like motion and interaction with the environment, has substantial effects on BAM and SEC.

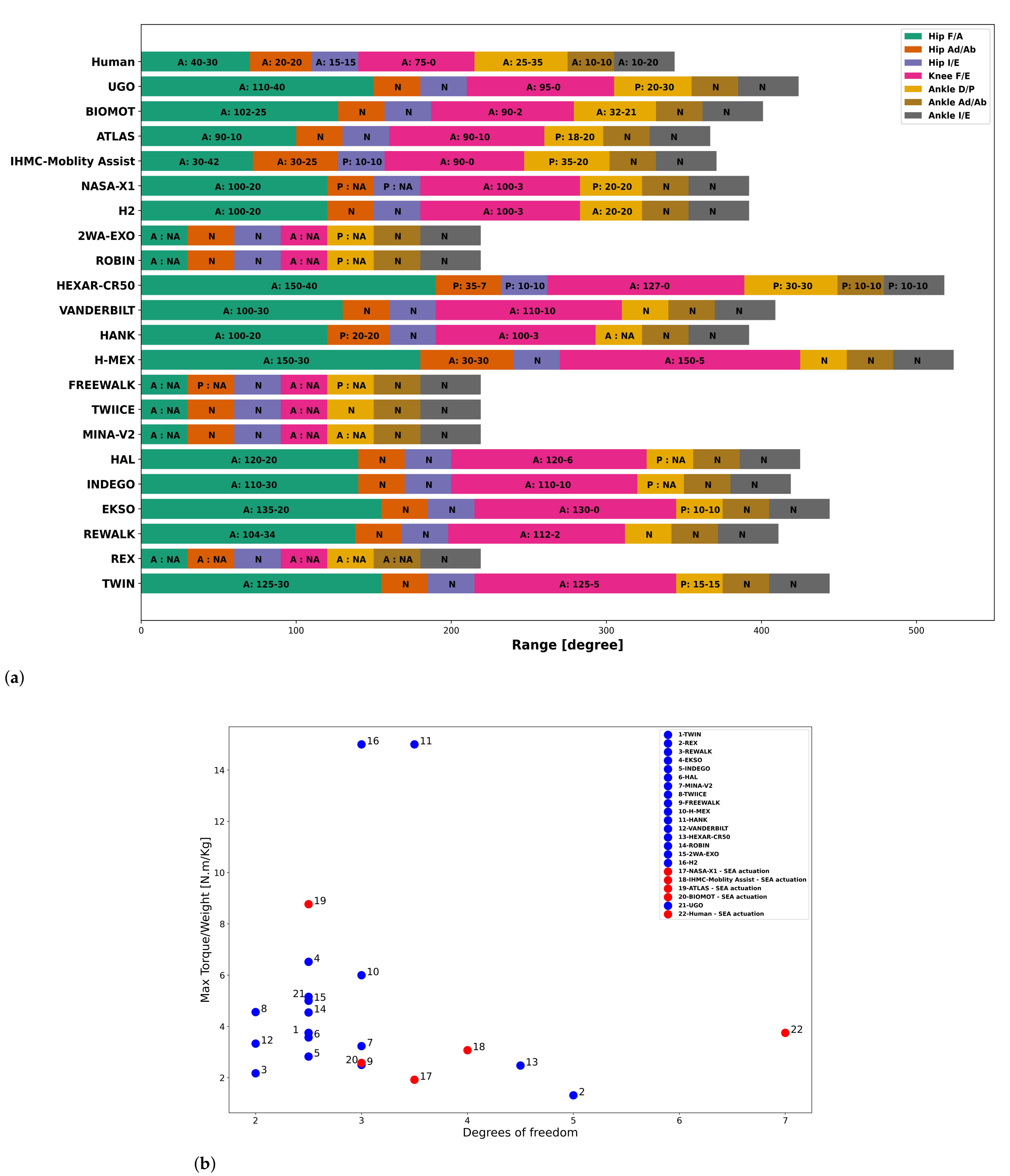


Figure 7. (**a**) RoM of actuators for various PLLEs. A—Active joint, P—Passive joint, N—No joint, NA—information is not available. The x-axis represents the range in degrees. (**b**) Ratio of PLLE maximum torque of motors to overall weight of the exoskeleton as an indicator for deliverable power, w.r.t DoF of each leg. Passive joints are considered to have 0.5 DoF. Blue circles depict stiff joints and red circles joints with SEA actuation. Human biological lower limb is considered to weigh 40 kg and provide 150 Nm torque. We considered 50 Nm torque for PLLEs with unknown max torque value.

4.2. Control Algorithms and Strategies

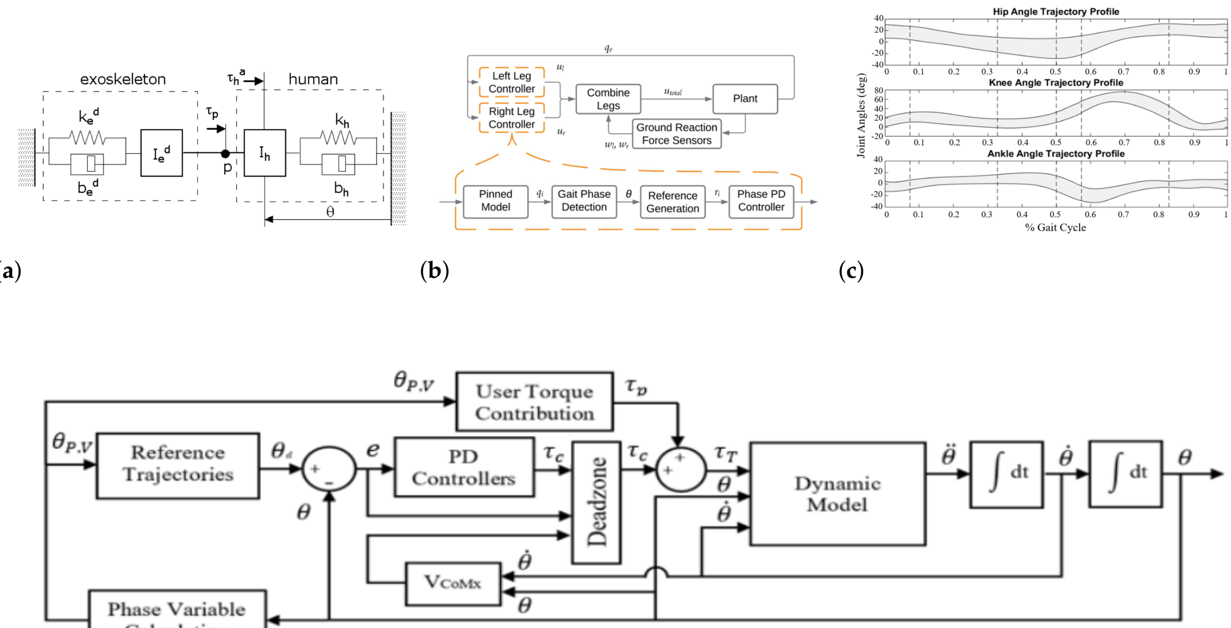
Control strategies play a fundamental role in the mobilization of the PLLE and the patient as a whole. To date, many different control strategies have been proposed in the field of PLLEs. In this section, we group these control strategies and evaluate their advantages w.r.t the criteria we defined before. We categorize control strategies based on their relevance in addressing rehabilitation aims and also in accomplishing ADL.

We differentiate them into following four categories: (I) assistive, (II) challenge-based, (III) volitional and (IV) autonomous controllers. In Table 2, we list a number of recent and promising works that represent interesting assistive, volitional and autonomous controllers. Please note that we could not find recent works compliant with our topic-specific criteria according to Figure 1 for challenge-based controllers.

4.2.1. Assistive Controllers

Assistive controllers aim for partial or complete assistance of the patients that comes in different frameworks as depicted in Figure 8, and are mainly in the following forms:

- Trajectory-based (position, velocity);
- Force/flow field;
- Impedance and admittance;
- Virtual constraints.



(**a**) (**b**) (**c**)

(**d**)

Figure 8. Assistive controllers: (**a**) Linear model of the coupled 1-DOF human–exoskeleton system [106]. (**b**) Hybrid zero dynamic-based controller supplemented with foot detection-based switching condition [107]. (**c**) Performance of the proposed controller acting on paretic leg in forcing the trajectories back into the deadzone throughout gait [108]. (**d**) AAN controller with the user torque contribution for different gait pathologies [108].

Please note that the aforementioned assistive controllers are low-level controllers that may be adopted in other categories with an appropriate mid/high-level control framework. However, they are the common types of assistive controllers.

Trajectory-based controllers are widely adopted, especially in commercial devices, to ensure a stable walking pattern [109–114] and mainly promote SEC criteria. In these controllers, a predefined trajectory or pattern is regulated to fit patient-specific walking pattern requirements. Trajectories are usually based on biological walking patterns of humans in either the task or joint space. A low-level controller, usually a PID controller, is responsible for tracking the motor position/velocity trajectory with respect to time or the phase of the gait. These controllers provide full assistance to the patients for all walking modalities from sit-to-stand to walking. Trajectories are predefined for the whole walking time and patients are able only in some cases to start or stop a step through adjusting trunk tilts or sending manual commands.

The *force/flow field* control modality partially assists the patient in tracking the predefined trajectory in the context of assistance-as-needed [115–120]. These controllers allow patients to contribute to walking by inserting forces at any phase. Therefore, in this control modality, patients are allowed to deviate from the main trajectory, which can be predefined or designed online, to an admissible extent that is bound within a limited zone.

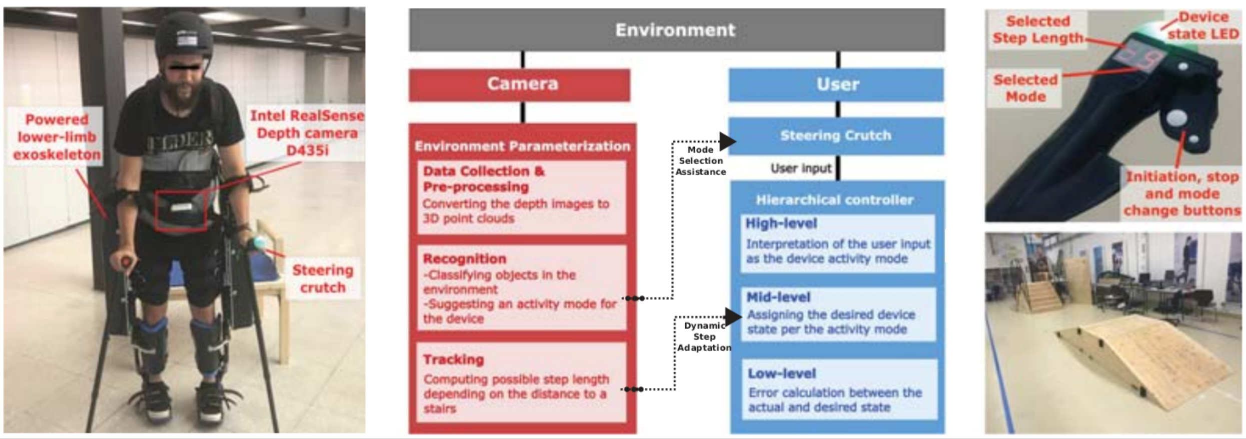
Table 2. Description of the methods that some selected works implemented for assistive, volitional, or autonomous control strategies on PLLEs.

Strategy	Ref.	Method	Description
Assistive	[121]	Impedance	Implemented an adaptive impedance controller by introducing an adaptive control law that considers interaction torque of human–exoskeleton. A radial basis function neural network was adopted to approximate the uncertain dynamic.
	[114]	Tracking	Developed a parameter identification system for both human and exoskeleton and adopted linear quadratic programming method for trajectory tracking.
	[118]	AAN	A velocity field in task space was constructed to determine motion velocity limits at any configuration, and implemented a force field controller in joint space, embedding a tunnel for position tracking and control.
	[120]	Torque field	Proposed a torque field controller to guarantee coordination between limb joints and also allows the user to vary step length and time.
	[108]	Virtual constraints	Proposed a virtual constraint model to generate trajectories autonomously and to ensure stability of the user. This work adopted also AAN method to allow the user to deviate from desired trajectories within a deadzone that is defined according to velocity of CoM.
Volitional	[122]	BMI	Implemented a control framework to feed human detected intentions to the PLLE considering safety issues. This work successfully detects six different intentions.
	[123]	HMI	This work combined EEG and EMG signals to detect three movement classes of human intentions.
Autonomous	[124]	Synergy	An adaptive synergy-based control is developed to realize impedance adjustment on affected leg following the kinesiological information of healthy leg.
	[125]	Balancing	A safety index based on extrapolated CoM of human–exoskeleton model together with dynamic movement primitives is presented to promote BAM and control of exoskeleton.
	[126]	CoG transfer	It presents a control scheme capable of minimizing the reliance on pilot for transferring centre of gravity. It also provides an online trajectory planning considering CoG transfer and safety.

Virtual potential fields, corresponding to deviations from the main trajectory, are created to guide the limbs toward the reference pattern. The force potential field [127,128] acts as a virtual wall for the motion of the legs, allowing the legs to move within a bounded area and not exceed that area. It is mainly formed of tangential, normal and damping terms. Tangential and normal forces are regulated w.r.t tangential and normal distances between the current and desired trajectories in the configuration space, while the damping force limits the velocity of the leg. Normal forces push the leg toward the desired trajectory, whereas the tangential forces help the leg to track the desired trajectory. Flow potential fields instead create a viscous fluid field and the force control is calculated relatively to the Euclidean distance of the actual velocity from the desired velocity and limit the velocity of the motion of the legs corresponding to the gait phase. Force/flow field controllers promote physical engagement of the patients in gait and also provide a sort of DEM ability for patients. However, superiority of this approach over conventional methods (assistive controllers) for GAR is not confirmed yet [72].

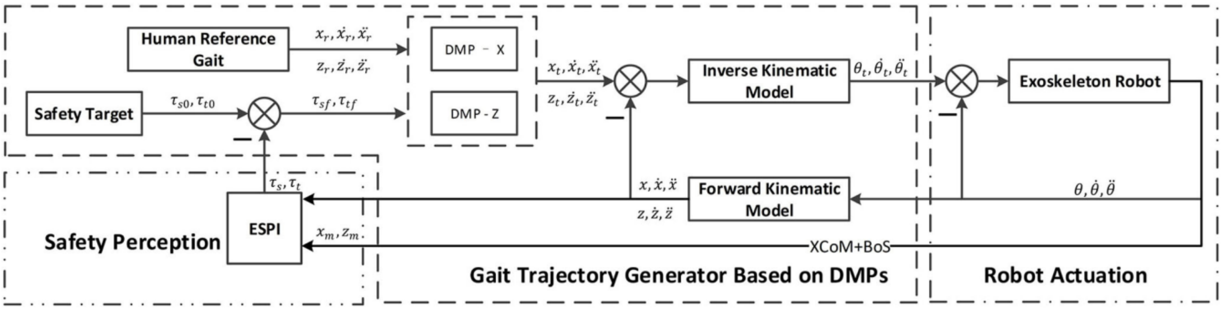
Controllers based on *impedance/admittance* are highly beneficial for PLLEs [121,129–131], since the soft physical contact of PLLEs with the user and also the hard GRF acting on user soles, specifically while walking on uneven terrains or crossing obstacles [106,129], demands impedance/admittance controllers to track the predefined trajectory well. The main objective of the impedance controller is to minimise the influence of external forces on the PLLE and ensure motion trajectory tracking. The impedance controller simulates the interaction forces as mechanical impedance. The controller, following the impedance model, generates forces and applies them to the perturbed PLLE to both guarantee a proper position control and also dissipate the effect of external forces [132]. In admittance control, on the other hand, the controller has the role of mechanical admittance and the PLLE is considered as mechanical impedance. Thus, the admittance controller, by following the impedance model and observing external forces, generates desired position motions and sends them to the PLLE for position control. Impedance-based controllers are essential for SEC, as they consider physical interactions between the user and the environment. They also have shown positive effects on GAR in SCI patients [133].

Virtual constraints control methods make it possible to virtually add limits to some parameters or shape the output trajectories to meet specific constraints [108,134–137]. This method provides inputs considering the actual state of the PLLE and also satisfying predefined virtual constraints. Therefore, in contrast to trajectory tracking, these methods can deliver online and stable trajectory solutions that take inter-limb coordination problem into consideration. Defined constraints are usually kinematic functions such as desired forward velocity, or dynamic functions such as desired angular momentum to follow. These constraints applied with the physical constraints, that is, the dynamic model of PLLE together with the wearer, yield dynamic and stable solutions in the presence of uncertainties. Moreover, the controller is not time-dependent and it mainly depends on the states of the system. An overview of the lower limb exoskeleton shared control system can be found in Figure 9.



(a)

Figure 9. *Cont.*



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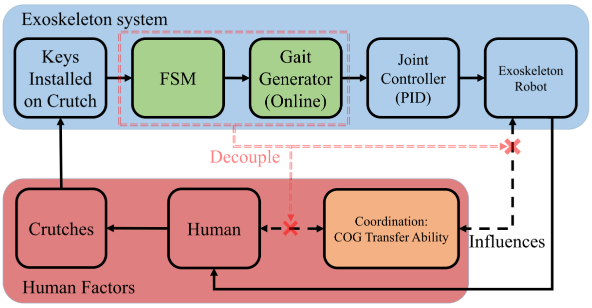

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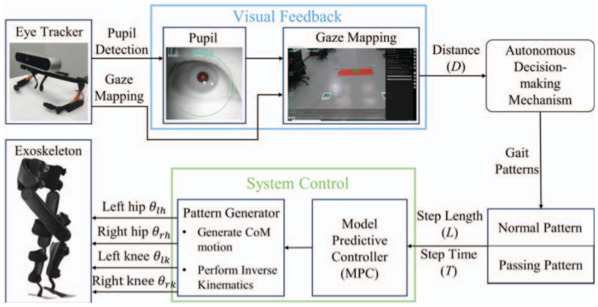

(**d**)

Figure 9. (**a**) Overview of the lower limb exoskeleton shared control system [138]. (**b**) The architecture of the balance control strategy presented in [125]. (**c**) Control structure of the human–exoskeleton system [126], (**d**) Autonomous gait pattern planning framework presented in [139].

4.2.2. Challenge-Based Controllers

Challenge-based controllers aim to increase the physical engagement of the patients rather than partially or fully assist them. They can increase the difficulty of the training task, or oppose the movements of the limbs. This can be achieved through various strategies such as resistive training, error augmentation, inducing constraints and applying perturbations [140]. Resistive training adds resistance to the movement of the paretic limb of the patient as a mean to increase muscle strength [141–143]; however, this method does not lead to improvements of functional skills.

The error augmentation method was proposed to promote implicit learning and motor adaptation capacity, that is, the capability of modifying motor commands to archive desired motions. Error augmentation is accomplished by applying forces to the limbs in order to push them away from approaching to the desired trajectory. Usually a force/viscous potential field is adopted to generate the disruptive force opposite to assistive force/viscous field forces. This method has proved to be efficient in motor adaptation [144–149]. Another approach to challenge and engage the patients is to induce constraints on intact limbs so that the patient relies more on affected limb. Induced constraints promote and enforce symmetric use of limbs in walking [150,151].

It is noteworthy to mention that challenge-based controllers have rarely been studied and adopted despite the diffusion of PLLEs in robot-assisted therapy in recent years. However, these methods in traditional therapies have been widely used and have proved to be efficient in achieving positive GAR outcomes in the studies mentioned above.

4.2.3. Volitional Controllers

A possible alternative to keep patients cognitively engaged to promote GAR, and allow them to participate in DEM for accomplishing tasks, is to introduce a higher level of controllers that include the intention of patients in controlling PLLEs. Volitional controller frameworks embed at least two hierarchical levels of control: one to identify the intentions of the patient and the other to integrate and implement the intentions that can be related to any of the assistive or challenge-based methods we introduced previously. Intentions can range from walking pattern adjustments such as step length and velocity, to switching between LOMs. Intentions are mainly detected using sensory data or patient manual inputs. These sensors can be categorised into physiological sensors such as electromyographic (EMG) and electroencephalographic (EEG) that detect intentions prior to patient movements, proprioceptive/exteroceptive sensors such as IMU, GRF, and camera sensors that provide intention information after the movements. Various algorithms have been proposed to exploit the acquired data and transform them to meaningful actions. Various control schemes also have been developed to integrate human intentions to the low-level controllers to ensure stable and safe locomotion.

Methods based on EEG signals [122,123,152] attempt to recognise human intentions in the context of brain–machine interaction (BMI), adopting different classifiers such as linear discriminant analysis (LDA) and Gaussian mixture model (GMM). However, the problem with these methods is the reliability of signal acquisition and precision of the classifiers. EMG-based intent recognition also has its own problems, since reliability of the signals and robustness of the classification methods have excessive reliance on the placement location of EMG electrodes and user-specific adjustments. Therefore, EMG-based models are frequently employed in conjunction with other sensors such as GRF and IMU [153–157].

Human-recognised intentions at their best efficiency are not enough to independently drive PLLEs. Therefore, results of the recognition are usually limited to follow specific state transitions of control frameworks such as finite state machines (FSM).

4.2.4. Autonomous Controllers

Autonomous controllers are more adaptive and consider the environment, kinematics and dynamics of interactions and human posture effects for gait pattern design and control, compared to what discussed previously, [124,158–168]. These controllers have more complex schemes and are composed of different layers, including perception, high-level for decision making and low-level control for gait generation and actuation. These controllers aim at assisting patients, either fully autonomously or by means of human-in-loop strategies, with ADL rather than rehabilitation goals. These controllers aim at integrating different control modalities to promote flexibility in HMI and ensure safety and SEC.

The work presented in [138] provides a shared level of autonomy and control with the patient. In that work, a vision perception system is actively monitoring the environment for possible variations in LOM and shares the adaptation strategies with the patient for their further decisions as shown Figure 9a. It also provides adaptive step length adjustments for the user based on environmental conditions.

A recent work [125] introduced a safety index to generate adaptive solutions for gait patterns considering human balance and also exploiting reference trajectories. They used a framework, as shown in Figure 9b, to observe the integrated model of PLLE together with the user and by considering a safety and balance index, generate safe targets. They proposed a novel theory to trace the overall CoM of user and exoskeleton online and evaluate the safety and take further actions. A different approach for online gait pattern design was implemented in [126]. That work addressed the limitations of CoM transfer from one foot to another to start a step for paraplegic patients. The authors of that work introduced a control scheme as shown in Figure 9c, where the motion of patient and exoskeleton are separated and using a finite state machine, CoM transfer is accomplished in specific states of a step to relieve the patient of relying on CoM transfer for the initiation of a step.

Different approaches such as vision-assisted gait pattern generation [139], within more sophisticated control schemes, Figure 9d, have been proposed and implemented. Although many of these works proved to provide stable solutions for assisting patients, still their safety concerns and their reliance on extra instruments, uncertain reliability and robustness, and more importantly, the cognitive load and stress of the patients, make them less popular.

4.3. Augmented Devices and Sensors

Augmented devices, to date, are rarely adopted for assistive applications of PLLEs, and mainly are used for research purposes. However, their role can potentially increase the efficiency of PLLEs and provide additional functionalities for human locomotion. In the following part we list some of them that are widely used.

4.3.1. Functional Electrical Stimulation (FES)

The use of functional electrical stimulation (FES), either with PLLE or alone, for both gait rehabilitation aims [169] and assistance of ADL, has proved positive outcomes as shown in a review paper that gathered together all the rehabilitation benefits of FES [170]. Studies in [171] showed slight improvements in gait performance (speed, stride length and cadence) of patients with SCI lesions. Another study [172] presented more interesting results of using FES in reducing spastic muscle tone. FES can also be employed to assist the exoskeletons in the propulsion of patients. Stimulation of muscles generate metabolic energy and can be harvested to reduce the energy consumption of the PLLE during different LOM and gait phases [173–178].

However, recruitment of FES with PLLEs includes many challenges and limitations as follows: (i) stimulated muscles generate forces with random values that vary in time and for each patient, (ii) muscles go through physical fatigue after a certain time and dosage and (iii) difficulty in electrode placement for specific muscle groups. However, the use of FES with PLLEs has grown recently and different control frameworks have been proposed to overcome these limitations [179].

4.3.2. Sensors

Various sensors such as inertial measurement systems (IMU), GRF sensors, force and pressure sensors and distance measuring sensors have been adopted to measure different aspects of kinematics or dynamics of the interaction between patient and PLLE. IMU sensors are mainly used to detect the position of body segments, phase and event detection and also for LOM detection [180–184].

GRF and pressure sensors are usually placed on the soles of the shoes and provide information about the vector of interaction forces with the ground. These data are used to find CoP for BAM and proper control of the PLLE [185]. They also provide information on foot configuration relative to the ground [186], or directly being used for force control methods [187]. Mechanical sensors play complementary roles within different control schemes to promote BAM and DEM criteria.

4.3.3. EEG/EMG Sensors

EEG signals are widely used to measure brain activities in BMI systems with respect to their counterpart methods. This is due to their non-invasive monitoring and portability, and that they can be easily placed on the scalp to monitor brain activities. Different methods have been developed to detect neural features relevant to movement and walking [188]. EEG signals are classified based on range of frequencies, where each range represents a certain type of activity. For instance, EEG signals with range of 13–30 Hz, known as beta rhythm, represent activities regarding to movements, preparation for a movement, planning and imagining a movement [189]. Movement-related cortical potential and event-related desynchronization features are two major techniques used for movement activities detection [158,190–192]. The problem with EEG signals are the artifacts related to eye motion, cardiac activity and scalp muscle contraction [193]. They also suffer from high complexity that renders the feature extraction process error prone and time consuming. Another limitation of EEG signals for driving PLLEs is the separation of patterns regarding intention and motion of different legs since the motor cortex area of legs are quite close to each other [123]. Furthermore, long-term prior training is required for non real-time feature extractions that are composed of mainly 2–4 classes, including move, stop and turn left/right commands [190,191,194,195]. Reliability and real-time control of EEG signals to drive PLLEs, to date, remains challenging. Therefore, in many studies, EMG signals are integrated to better address BMI issues. However, BMI methods are extremely useful for DEM and have proved to be efficient in improving motor recovery and GAR [192].

EMG signals detect voluntary muscle contractions prior to muscle movements and provide information on muscle forces [196,197]. EMG signals, compared to EEG signals, have higher signal to noise ratio and have less time delay [198]. However, finding mapping models for EMG signal data and estimated active joint torques is challenging [199,200]. Additionally, electrode displacements, the time-varying property of EMG signals, and the problem of recalibrating the EMG-torque models after doffing and donning, limit their applications [201].

4.3.4. Smart Crutches (SMC)

As discussed in Section 4.1, the majority of complete PLLEs lack the actuation in the frontal plane and miss the ankle actuation in the sagittal plane. Therefore, users of PLLEs need to use crutches or walker to transfer their body weight and maintain balance. Moreover, they can be equipped with additional sensors and controls to provide more information on human motion. However, a limited number of PLLEs and researches employed smart crutches in their platforms. Smart crutches can potentially benefit PLLEs for different control schemes and establish a human machine interaction mean. Smart crutches employed in [202], exploit force sensors attached to the bottom of the structure to estimate GRF and IMU sensor to gain information on the placement distance for further step length control. A similar work [203] adopted strain gauges to measure GRF to feed the inverse dynamic model. The study presented in [204] attempted an online gait planning based on calculation of CoP exploiting GRF coming from smart crutches and also GRF from human-machine complex. Moreover, smart crutches are important for providing additional information on human–exoskeleton posture, therefore promoting DEM and SEC by adopting different control schemes.

5. Discussion

Evaluating the performance of PLLEs considering only parameters related to exoskeletons may result in incorrect conclusions. Moreover, the evaluation requires a large search space including all one-to-one or many-to-one relationships among all parameters and the performance index. Furthermore, physical characteristics and skill of the users may heavily influence the efficacy of the results. Our proposed method , besides the effects of exoskeletons, considers the effect of control algorithms and accessories on the performance evaluation process. Moreover, our method attempts to narrow down the large-space of the parameters into a small set of functional criteria that directly evaluate the rehabilitation and assistive performance of the PLLEs isolating the wearer-related impacts. Our proposed criteria, includes all the rehabilitation and assistive aspects as ultimate goals of PLLEs. However, the application of our method is limited to qualitative performance evaluation and for benchmarks, competitions or comparative evaluations, further quantifying mappings are needed to be integrated to this method.

Additionally, we conducted a review to identify the *major factors* that were reported to have high impacts on our selected criteria. We also introduced different *parameters* of PLLEs, i.e., aspects of exoskeletons such as kinematics, actuation and design, different types of controllers and various augmented devices that can be optionally utilized. To address the performance evaluation issue, based on accomplished studies and reviews in the literature, we performed an analysis on how those parameters of PLLEs can promote the major factors of our proposed criteria, and ultimately how performance of PLLEs is improved.

6. Conclusions

In this paper, we reviewed and analysed PLLE platforms including different design choices from PLLEs, control strategies and auxiliary devices. To better address assistance and rehabilitation challenges, we studied neurological disorders and the adverse effects that they have on patients. We also defined a set of criteria that address assistance and rehabilitation purposes for patients with neurological disorders. For all aspects of platform, we thoroughly investigated how they can affect the outcome of performance evaluation criteria we defined. We also reviewed recent works that adopted these aspects and included their advantages in terms of assistance and rehabilitation benefits to support the factors that promote our defined criteria. Our study aims at helping researchers and engineers, who design PLLEs or develop control strategies for rehabilitation goals, to highlight the gap between current technologies and rehabilitation expectations and also to indicate possible directions for improvement. Rehabilitation using PLLEs requires deep and vast knowledge over design, engineering and neuro-rehabilitation that are not readily accessible for all researchers. Moreover, the observed convergence in the design and structure of PLLEs in recent years to similar solutions due to many different reasons such as technological barriers, certification problems and lack of investments in the area of rehabilitation robotics, hinder outstanding technological breakthroughs towards effective rehabilitation.

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