

Review on Control Strategies for Lower Limb Rehabilitation Exoskeletons

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ABSTRACT Research on lower limb exoskeleton (LLE) for rehabilitation have developed rapidly to meet the need of the population with neurologic injuries. LLEs for rehabilitation include therapeutic LLEs that aim to restore walking ability for patients, and assistive LLEs that offer support on activities in daily life. A substantial part of them can serve both purposes. However, these devices are yet to reach the final goal of performing human-machine joint movement agilely and smartly. Control strategy plays an important role in achieving their designed goal. At present, control strategies face three major challenges: how to detect human intention, how to do motion control with given intentions, and how to optimize control parameters to suit different individuals. As a contribution, this paper offers an overview on the state-of-the-art control strategies for rehabilitation LLEs by classifying them into eight categories, each of which is presented with a technical summary and tabulated information of representative papers. Moreover, current approaches addressing the three challenges are discussed in a macroscopic perspective. Finally, it has been explored which requirements the future control strategies should meet for maximizing the performance of rehabilitation LLEs.

INDEX TERMS Rehabilitation exoskeletons, lower limb, control strategies, rigid exoskeletons.

I. INTRODUCTION

Powered exoskeleton is a unique kind of assistive robot that possesses human-machine shared autonomy. On one hand, it respects human intention input and therefore keeps human in the control loop. On the other hand, it provides robotic guidance to human especially who needs motion assistance. Keywords 'exoskeleton' and 'powered' mean the device is built by rigid structure and it contains active joint(s) respectively [1]. Powered exoskeletons are categorized into human augmentation exoskeletons and rehabilitation exoskeletons. The former is used to enhance strength and endurance for military personnel [2] or people in the workplace [3]. The latter is used to regain movement ability for patients with neurologic injuries [4]. Further the rehabilitation exoskeletons are divided into therapeutic ones employed in rehabilitation therapy centers and assistive ones for assisting activities in daily life (ADL) [5]. This taxonomy is considering that the rehabilitation process often benefits from robotic assistance,

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as well as the assistive and the therapeutic exoskeletons share many similarities in mechanics, actuation, and control.

The earliest assistive LLE dates back to 1969, when researchers in Mihajlo Pupin Institute developed a pneumatically powered exoskeleton for persons with walking disabilities [6]. In 1976, a therapeutic LLE was born for physical therapist to provide tele-guidance to patients from a master exoskeleton [7]. Recently, commercialized devices have made robotics rehabilitation publicly available. For example, Lokomat (Hocoma, Switzerland) is a treadmill-based gait training device with dynamic body weight support and fixed trajectory repeating [8]. ReWalk (ReWalk Robotics, Israel) and Ekso (Ekso Bionics, USA) is also kinematically pre-programmed, but are more portable, thus serve both purposes of assisting ADL and rehabilitation therapy [9], [10]. Rex (REX Bionics, USA) and Atalante (Wandercraft, France) are cumbersome but self-balanced [11], [12]. Indego (Parker Hannifin, USA) is the only commercially available LLE with backdrivable actuators, and is originally developed in Vanderbilt University then out-licensed to Parker Hannifin [13], [14]. However, the efficacy of these exoskeletons control system

has yet to reach the desired level. First, although robotics interventions have reduced the need for human labor and have increased the average training time, whether the effectiveness of robotic-assisted rehabilitation surpass that of the conventional one is still inconclusive [15]–[17]. Second, the control strategy is not enough intelligent to achieve agility and embodiment. On the way to design smart control strategy, various explorations have been done, in which few were implemented in commercialized devices. Thus, this paper focuses on the control strategies for rehabilitation LLEs.

Previous reviews have covered rehabilitation LLEs generally [17], [18], or focused on aspects such as mechanics [19], medical evaluation [20], commercially available devices [21], and control strategies. One of the earliest and most cited review [22] highlighted many key aspects of control design such as walking phase separation. Tucker *et al.* [23] first draw a big picture of control strategies for lower limb assistive devices. Then subsequent reviews have summarized them according to different human-machine interfaces (HMI) [24], kinetic/kinematic control [25], or actuating different set of joints [26]. However, as advanced control strategies develop overtime, the categorization should be refined, rather than binary classification such as assist-as-needed / trajectory tracking or kinematic / kinetic control. Moreover, many ideas for control are shared across LLEs actuating different joints or that using different actuators or HMIs.

The scope of this review is the modern control strategies for lower limb rehabilitation exoskeletons. Specifically, on one hand, the reviewed exoskeletons 1) is composed of rigid links (exclude soft exo-suit), 2) contain at least one active joint (exclude unpowered exoskeleton), 3) assist human lower limb (exclude upper limb exoskeleton). In contrast with unpowered exoskeletons [27], [28] that utilize passive dynamics to assist human locomotion, powered exoskeletons can leverage active control strategies, which reshape the dynamics of the human-machine system into a desired form. Soft exo-suit and rigid exoskeleton are two important types of assistive robot. The former is promising to achieve comfortable, light-weighted, and backdrivable assistance [29], [30]. While the latter can offer greater assistive torque, offload the body weight and output torque to the ground, and thus suits patients with more severe lower limb impairments [31]. For more information on exoskeletons that are beyond the scope of this paper, readers are referred to [1], [32]. On the other hand, control strategies are categorized according to similarities within the whole strategy, which encompasses 1) HMI input; 2) high-level trajectory optimization or selection; and more emphatically 3) the mid-level core control algorithms; and 4) low-level kinematic or torque tracking. Each control strategy targets at neither one specific actuator, nor one set of actuated joints. It is also not restricted by the type of HMI input. But given that the actuator and sensor input does have a great impact on controller design, how to select the appropriate strategy for a particular set of hardware is also discussed.

The contribution of this paper include: 1) as a paper dedicated to review control strategies of rehabilitation LLEs, eight categories of control strategies are listed to summarize the state of the art; 2) general frameworks in various form for capturing a big picture for every category are proposed; 3) current approaches addressing the three challenges—human intention detection, motion control, and control parameter optimization—are discussed in a macroscopic perspective.

The remainder of this paper is organized as follows. In section II, the control strategies are sorted into eight categories. Within each of the category presentations, technical overview with the aid of mathematical expression or figure illustration is reported. Moreover, details of typical papers of these control categories are listed in Table 1. In section III, the state-of-the-art controller is discussed in a different perspective that features three key elements: sensing technologies, motion control algorithms, and optimization techniques. The future expectations of LLEs are also considered. In the end, Section IV concludes this paper.

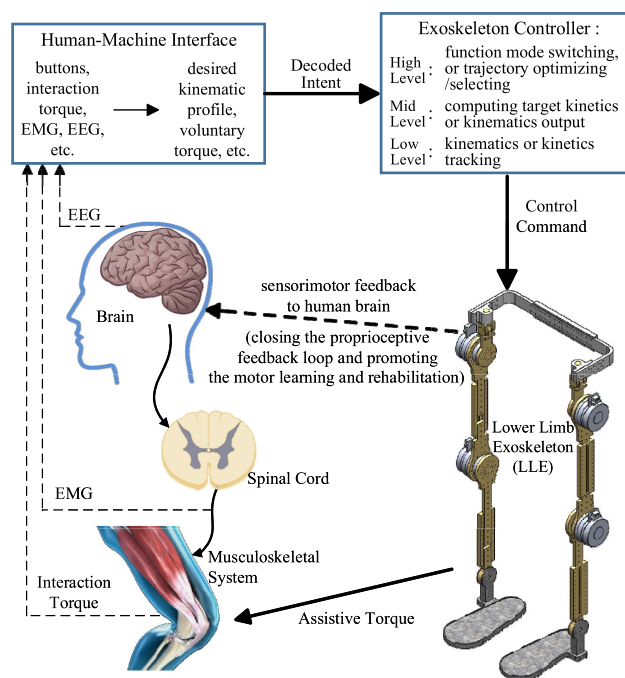


FIGURE 1. General framework of control strategies for lower limb rehabilitation exoskeletons.

II. CONTROL STRATEGIES FOR LOWER LIMB REHABILITATION EXOSKELETONS

The general framework of control strategies is shown in Fig. 1. The controller takes human intent decoded by HMI as input and drives the LLE to provide assistive torque. The raw human input can be collected from neural signals along the descending tracts, or physical input such as interaction torque and pressing buttons. The human intent can be estimated as discrete commands such as walk/stop or continuous signal such as desired kinematic profile and voluntary joint torque.

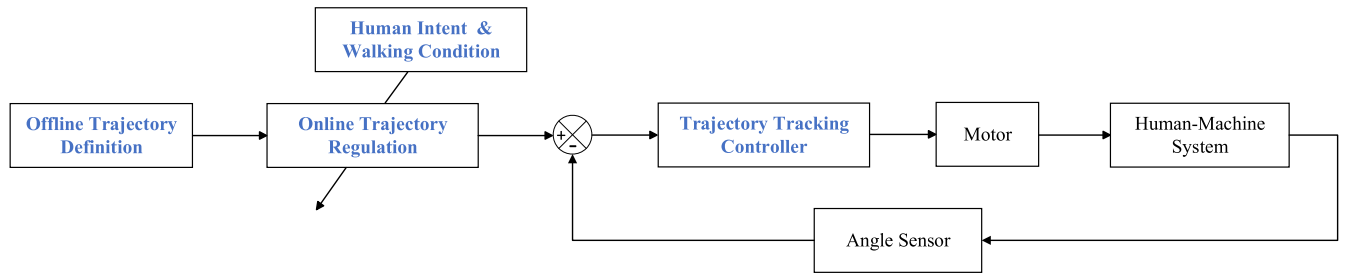


FIGURE 2. General framework of trajectory tracking control.

For the controller of exoskeletons, usually a hierarchical structure is adopted. Some papers emphasize high-level trajectory planning, while some highlights mid-level kinematics or kinetics computing. Importantly, with these control strategies, the LLE is able to generate human-machine joint movement and thus provide sensorimotor feedback that echoes the original human intention. This closes the proprioceptive feedback loop and therefore promotes motor learning and rehabilitation.

Within this general framework, hereby the control strategies are further divided into eight categories, each of which are presented as follows.

A. TRAJECTORY TRACKING

1) BRIEF OUTLINE

- 1) Purpose: perform movement tasks without assuming any motor ability of human.
- 2) Concept: make the actuated joints follows a predefined trajectory.
- 3) Advantages: versatile enough to perform activities in daily life; simple implementation.

Among many control strategies for rehabilitation LLEs, one of the simplest approaches is trajectory tracking, which is to replay a predefined position or velocity profile on the actuators. As shown in Fig.2, it often incorporates three parts: offline trajectory definition, online trajectory regulation, and real-time trajectory tracking. The offline trajectory definition can be accomplished by manually setting the position profile such as sinusoidal curve [33], or modified from gait data of healthy subjects [34]. But these simple definition does not guarantee balance without crutches. Some method also used offline optimization techniques to take individual information and balance maintenance into consideration [12]. The online trajectory regulation part often includes, from macro to micro, safety guard for ensuring the trajectory is in the acceptable region, finite state machine (FSM) with human intention or walking condition input for selecting the optimal trajectory to replay, and parameter alteration for adapting the trajectory to the real walking scenario. For real-time trajectory tracking, PID control is a common choice, and is often built in the low-level motor driver [35]. Other choices including sliding mode control, LQR, or model-based controller with disturbance rejection. To date, the trajectory tracking control has

been adopted by many commercialized exoskeleton such as ReWalkTM [9], EksoTM [36], ExoMotusTM, etc. Moreover, it is also widely used in the Powered Exoskeleton Race session of a unique competition – Cybathlon [37], [38]. The result of the competition (e.g. Mina v2 [39], [40], SG Mechatronics [41]) shows that the trajectory tracking method can enable patient with complete lower limb paralysis to perform ADL with crutches to maintain balance.

B. ADMITTANCE SHAPING

1) BRIEF OUTLINE

- 1) Purpose: make the LLE compliant to interaction torque or voluntary muscle torque.
- 2) Concept: reshape the intrinsic admittance of the LLE.
- 3) Advantages: simple one-DoF dynamics model, compliance, encourage voluntary muscle recruitment.

Admittance shaping has been extensively applied to robots which inevitably interacts with external environment. From the perspective of human especially with muscle weakness, it can alter the dynamic response of the wearable devices and even render it assistive to intended motions. Methods for admittance shaping include admittance control and impedance control [42]. Admittance control refers to control structures that use a virtual admittance that takes effort as input then outputs desired flow. The desired flow is further tracked by an impedance (i.e. trajectory tracking controller) to generate effort on the intrinsic admittance of the controlled object. While impedance control refers to controllers which directly generate effort on the controlled object using impedance model. Despite similarity, admittance control has been widely adopted for LLEs because of its good performance in soft contact environment [43].

Inspired by the work of Keemink *et al.* [44] and Nagarajan *et al.* [45], hereby a admittance shaping framework dedicated for LLE is proposed, as shown in Fig.3. The framework takes two variations into account: whether interaction torque or voluntary joint torque is inputted to the admittance model; and whether predefined trajectory is required for the admittance model.

The human-machine system is shown in Fig.3(a), The goal of this admittance shaping controller is to reshape the apparent exoskeleton admittance Y_a in order to make the dynamic response of the exoskeleton assistive to the human motion.

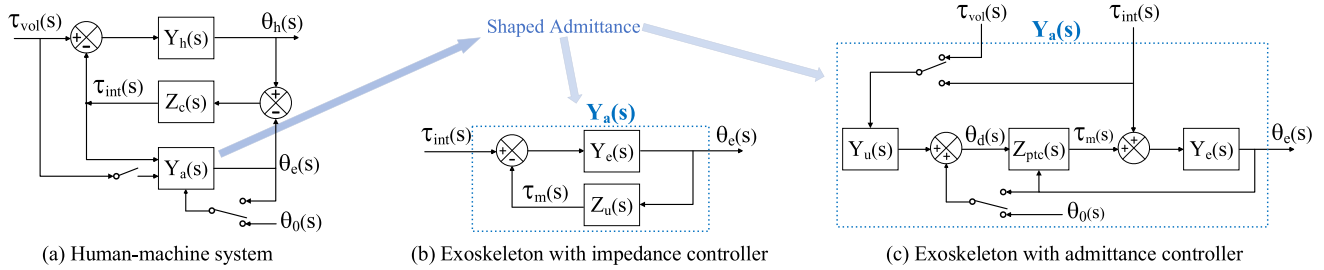


FIGURE 3. Framework of admittance shaping. where τ_{vol} and τ_{int} represent voluntary muscle force and interaction force; θ_0 , θ_e , and θ_h represent desired joint angle, actual joint angle of LLE, and the actual human joint angle; Y_h , Y_e , Y_a , and Z_c represent the intrinsic admittance of the human limb, intrinsic admittance of the LLE, apparent admittance of the exoskeleton felt by the wearer, and the soft coupling impedance; θ_d , τ_m , and Y_e represent the desired angle calculated by the admittance controller, the motor torque output, and the intrinsic admittance of the exoskeleton. Y_u , Z_u , and Z_{ptc} represent the admittance controller, impedance controller, and position tracking controller.

Y_a is expanded to either the system in Fig.3(c) with admittance controller or system in Fig.3(b) with impedance controller.

In Fig.3(b), the virtual impedance $Z_u(s)$ must be negative to render the device assistive [45]. But the parameters of this negative impedance should be carefully designed not to induce instability since it introduces positive feedback [45].

When the key is switch to θ_0 (i.e. control with predefined trajectory) in Fig.3(a) and accordingly Fig.3(c), the overall effect of this control scheme is allowing the wearer to move around the equilibrium point but at the same time attracted to this point [46], [47]. When the key is switch to θ_e (i.e. without predefined trajectory) in Fig.3(a) and accordingly Fig.3(c), the wearer is able to move freely with the reshaped exoskeleton dynamics [48], [49].

When the key is switched to τ_{int} in Fig.3(c), and accordingly the switch of τ_{vol} in Fig.3(a) is off, the virtual admittance $Y_u(s)$ takes the interaction torque as input. When the key is switch to τ_{vol} (i.e. muscle voluntary force as controller input), wearers do not have to push on the exoskeleton after counteracting their own limb’s inertia and gravity. Instead, the dynamic response of the device is directly according to the muscle force [50], [51] or even muscle force intention only [52], [53]. It can also be deemed as reshaping the admittance of the human-machine system [54].

Regarding the virtual admittance controller, a second-order inertia-damping-stiffness model is sufficient to emulate the desired behavior. Although the implementation of damping and stiffness shaping is simple [55], [56], inertia compensation is often sophisticated [57], [58]. Promising results have been achieved by paper [45], [59]. For more guidelines on reducing apparent inertia readers are referred to paper [44].

C. CONTROLLERS UTILIZING BACKDRIVABILITY

One of the properties of the exoskeleton joints is backdrivability, which measures how much torque a person needs to apply on the joint to reverse it. Backdrivability of joints can be achieved by either the unique mechanical design of actuators or some specific controllers such as admittance shaping and zero-torque control. But the problem of limited bandwidth has been shown for controller-implemented

backdrivability [60]. Recent years have witnessed several LLEs with backdrivable actuators, including Vanderbilt exoskeleton [61], a knee exoskeleton by Wang *et al.* [62], and a knee-ankle exoskeleton by Zhu *et al.* [63], etc. Among them a common choice to obtain backdrivability is quasi-direct drive actuator, which is compliant through the lack of inertia of the motor. Interestingly, backdriving the motor results in harvesting energy and prolonging the battery life. There have been literature that aimed to provide guidance on how to design actuators [64] and the whole mechanics of the robot [65] to improve backdrivability. Without going deep into details of actuator design, this chapter aims to summarize the control strategies that fully utilize the mechanical backdrivability of the exoskeleton joints.

Given the fact that the expected users of backdrivable exoskeleton still have partial abilities to move the affected leg, one of the simplest approaches in this category is using FSM to provide assistance only when necessary, and allowing the user to voluntarily move the limbs in the rest of the time. Murray et al. has proposed a control strategy for patients with lower limb hemiparesis [66]. The controller consists of three types of behaviors: gravity compensation, feedforward movement assistance especially when reversing or initiating lower limb movements during swing phase, and knee joint stability reinforcement. The assistance strategy was designed without specifying spatiotemporal trajectories such that users should help themselves to maintain balance and select step length.

1) VIRTUAL-FIELD-BASED CONTROL

a: BRIEF OUTLINE

- 1) Purpose: provide both gait guidance and assistance.
- 2) Concept: impose a virtual field to the configuration space of LLE.
- 3) Advantages: allow step-to-step variance, encourage voluntary walking.

Virtual-field-based control explicitly guide patients to a suitable gait trajectory. The virtual field can be in the form of torque field or flow field [67]–[69]. The torque field is equivalent to a spring-damper system that connects an arbitrary point in the configuration space perpendicularly to the

desired path, and thus it will always pull the leg normal to the path. The damping and stiffness coefficients are adjustable. Specifically, when the damping coefficient is zero, the control scheme can be regarded as an artificial potential field, where torque is the gradient of the field.

In contrast, flow field offers both guidance and assistance and combines them into one single component. The flow field is defined in order that the leg would be dragged by a flow force when the configuration point is immersed in a viscous fluid. Thus, the force exerted on the leg depends on the comparison between the real velocity in the state space and the reference velocity. It was further reported that the flow-field-based control can provide assistance to s DoFs in a m DoFs system, where actuated joints coordinate with unactuated joints [67].

2) ENERGY SHAPING

a: BRIEF OUTLINE

- 1) Purpose: provide partial assistance to voluntary human movement.
- 2) Concept: impose desired dynamics on the controller-plant system.
- 3) Advantages: allow free movement of wearer; task-invariant assistance.

Energy shaping is another control strategy that relies on backdrivable actuators. It imposes desired behavior on the controller-plant system. In contrast with admittance shaping which is only capable of reshaping the apparent dynamics of one DoF, energy shaping extends to reshape the whole actuated DoFs. This strategy has been explored in underactuated robotic systems such as bipeds [70]. Locomotor Control System Laboratory recently assessed the feasibility of using this strategy in the control of LLE with backdrivable motors [71]–[75].

In this control strategy, a relatively accurate dynamic model—underactuated model is needed for describing the exoskeleton side. It is generally expressed as:

$$M\ddot{q} + C\dot{q} + N = Bu + Bv \quad (1)$$

where M and C is the inertia and Coriolis matrix respectively, u and v is the torque input from the motor and the human respectively, N is the gravity vector, q is the generalized coordinates, and B maps the force input to all degrees of freedom. The three-dimensional position of the floating base and the angle of unpowered joints are typically underactuated degree of freedom. When deriving the dynamic equation from Lagrangian approach, however, finding the optimal generalized coordinates is sometimes complicated. Interestingly, this process can be simplified by defining holonomic constraints to eliminate redundant generalized coordinates. Specifically, Lin *et al.* [75] defined bilateral holonomic constraint to simplify different part of the lower limb as a fixed base during phase of heel contact, flat foot, and toe contact. It was in the form of:

$$M\ddot{q} + C\dot{q} + N + A\lambda = Bu + Bv \quad (2)$$

where A is the gradient of the constraint functions, and λ is the Lagrangian multiplier. From equation (2) different equivalent constraint dynamics for different contact phase is derived as:

$$M_\lambda\ddot{q} + C_\lambda\dot{q} + N_\lambda = B_\lambda u + B_\lambda v \quad (3)$$

The calculation of M_λ , C_λ , N_λ , and B_λ , along with the calculation of λ in (2) are referred to [76]. Interestingly, the control input can impose desired dynamics on the plant to shape the closed loop system as the following form:

$$\tilde{M}_\lambda\ddot{q} + \tilde{C}_\lambda\dot{q} + \tilde{N}_\lambda = \tilde{B}_\lambda v \quad (4)$$

In other words, this strategy can reshape the inertia matrix, Coriolis term, and gravitational vector to a required form. As a result, the apparent dynamics of the human-machine system is reshaped with respect to human input v . However, it cannot be reshaped arbitrarily. For two equations to be equivalent, a matching condition should be satisfied which determines what form of closed loop dynamics is achievable. Readers are referred to [70], [77] for more detail. The meaning of energy shaping is twofold. First, from the perspective of Euler-Lagrangian equation, the control input shapes the kinetic and the potential energy and regulates energy variation. Second, this strategy is closely related to passivity. The control input can distort the original passive vector field imposed on the state space to a desired vector field. Moreover, an energy storage value of the closed loop system is bounded by the input energy.

D. VIRTUAL CONSTRAINT

1) BRIEF OUTLINE

- 1) Purpose: perform movement tasks without assuming any motion ability of human.
- 2) Concept: use input-output feedback linearization to track an optimized time-invariant trajectory.
- 3) Advantages: guarantee stability along the trajectory; self-balance without crutches.

Virtual constraint was developed in the late 20th century for the control of bipedal robots largely thanks to Byrnes *et al.* [78]. Impressive results have been achieved by implementing this control approach to bipedal robots [79], [80] and prosthesis [81], [82]. LLEs and bipedal robots share many challenges, e.g. having many underactuated degree of freedom especially that from the posture of the floating base, and state variables undergo discrete jumps when the foot contacts with the ground. A team mainly from Wandercraft company, Caltech, and university of Michigan [12], [83], [84] believes that translating the virtual-constraint-based control from bipedal robotics [85] to LLEs could lead to a next level of assisted human mobility.

Similar to energy shaping control strategy, an underactuated hybrid dynamics model that capture full body motion is needed. Firstly, assuming that the human and the machine is rigidly connected, then the Euler-Lagrange method is used to derive equations of motion (EOM) of the

human-machine system:

$$M\ddot{q} + C\dot{q} + G = Bu + J_{st}^T F_{st} \quad (5)$$

where the interpretation of symbols is similar to that of equation (1), except that the stance foot contact is in the form of Jacobian matrix J_{st}^T times contact force F_{st} . Secondly, within the EOM, the term of contact force $J_{st}^T F_{st}$ is calculated using holonomic constraint like that in energy shaping. Finally, a hybrid dynamics model will be set up by imposing a switching surface to the continuous dynamics. When the preimpact state meets the switching surface, it will be transitioned to the postimpact state by a precalculated reset map:

$$\Sigma : \begin{cases} \dot{x} = f(x) + g(x)u, & x \notin S \\ x^+ = \Delta(x^-), & x \in S \end{cases} \quad (6)$$

where Δ is the reset map, and S is the switching surface, which in the simplest case, can be defined as the ground clearance of the swing leg equals zero. Virtual constraint was then imposed on the hybrid dynamics system to attract the whole system to a zero dynamics manifold. Intuitively, virtual constraint is similar to a physical constraint that restrict the state in the state space to a certain time-invariant path. But differently, the power injected into the closed loop system by the virtual constraint is nonzero. Specifically, it is imposed by designing a set of outputs as desired trajectories with relative degree of two and/or desired speed with relative degree of one. For example, the most frequently used output function with relative degree of two is in the form of:

$$y = f(q) \quad (7)$$

Then an input output feedback linearization controller can be obtained by driving the output function asymptotically to zero:

$$u = u^* + v \quad (8)$$

where u^* is for linearizing $\ddot{y} = 0$, and v is for asymptotically driving the output function to zero. For example, the output dynamics by applying PD controller on v is:

$$\ddot{y} + K_d \dot{y} + K_p y = 0 \quad (9)$$

In this way, the zero dynamics manifold can be created with supposing the output function being identically zero. Additionally, the term partial hybrid zero dynamics (PHZD) means that the zero dynamics manifold is contact invariant and is derived by ignoring the output function with relative degree equals one. It is important to study PHZD because the stability of the designed trajectory can be examined on the reduced dimensional internal dynamics [12]. The problem of how to design a trajectory for walking with exoskeleton that is both stable and natural is in the domain of trajectory optimization.

E. OSCILLATOR-BASED CONTROL

1) BRIEF OUTLINE

- 1) Purpose: synchronize the assistance of LLE with actual human walking.
- 2) Concept: adaptively learn the periodic characteristics in walking.
- 3) Advantages: allows step-to-step variance; adaptivity of controller.

Oscillator-based control method features a set of or a single oscillator(s) that are used to synchronize the phase of the controller with the periodic-assuming gait phase. Oscillators are used to generate a limit cycle which synchronizes itself to the phase of actual walking. When the actual gait deviates from the prior orbit, the oscillator parameters will be adapted to maintain the synchronization [86].

The first paper applying the adaptive frequency oscillator (AFO) to LLE was by Ronsse *et al.* [87]. Afterwards that oscillator-based approach was mainly designed for hip joint exoskeleton [26]. Recently this method was further validated on single knee [88] or ankle [89] joint actuation and multi-degree-of-freedom exoskeletons [90]. Because the oscillators are robust to perturbation and can reduce the dimension of control input, in addition to assistive robots, it has also been used for autonomous robot locomotion. In fact, oscillators are closely related to the notion of central pattern generator (CPG). CPGs have been widely found in animals to render rhythmic motion [91], and based on the same principle it have been created for robotics control [92]. The frequently used oscillators for LLEs such as Hopf oscillator [93] and phase oscillator [87] are abstract oscillators which belong to the three main types of CPG architecture (the other two are recurrent neural network and half center oscillator) [94].

For example, Ronsse *et al.* [87] first applied the adaptive oscillator proposed by Righetti *et al.* [86] to a single hip joint exoskeleton. This method utilized a pool of oscillators, each of which learned the phase, amplitude, and frequency of each sinusoidal components. In this way the online Fourier decomposition was performed to estimate the real-time hip joint angle. This is similar to the notion of “limit cycle construction of arbitrary shape” described in [95], i.e. to use the aggregation of adaptive limit cycles to approximate the periodic joint angle curve. This approximation was further improved by kernel-based non-linear filter (NLF) adopted from [96] to output the estimated joint angle trajectory. Finally, a proportional force field controller was formed by attracting the current state towards the phase-leading estimated joint trajectory.

While most of the oscillator-based controller is for single joint actuation, Seo *et al.* use it to control GEMS exoskeleton with multi-degree-of-freedom actuation [90]. Firstly, IMUs and dead-reckoning method was used to obtain the real-time foot-to-foot distance, which was later sent to the oscillator as a forced input. Secondly, one of the techniques for improving the converging performance is to use a particularly shaped adaptive oscillator (PSAO), which means the basis function of

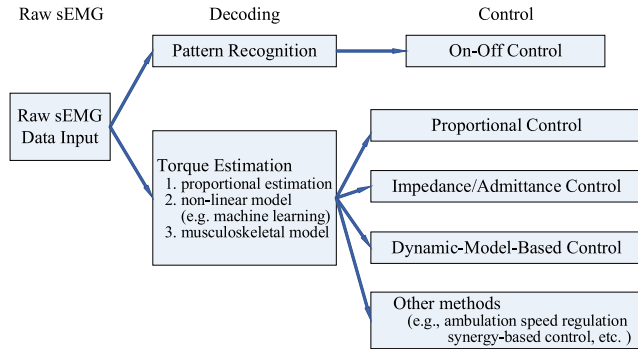


FIGURE 4. Categories of sEMG-based control.

the online Fourier decomposition is particularly shaped using prior information. For example, it was known beforehand that foot-to-foot distance curve resembles a cosine function, and thus it was then used to replace the basis function of the oscillator system. Thirdly, another technique is adding a coupling term of actual gait frequency detected by FSM to the equation of frequency learning rate. In this way the oscillator can benefit from a more accurate frequency signal capture by the widely used FSM method. Finally, the torque output was based on the estimated gait phase and the offline trajectory function, which was regulated by environment class and walking speed.

F. sEMG-BASED CONTROL

1) BRIEF OUTLINE

- 1) Purpose: control the LLE according to human intent decoded from surface electromyography (sEMG) signal.
- 2) Concept: various control method based on human intent decoded from electrical activities of muscles.
- 3) Advantages: direct volitional control; avoid electro-mechanical delay; wearers with severely impaired motor abilities can still command the LLE, as long as sEMG is detectable.

Controllers based on surface electromyography (sEMG) utilizes the measuring of electrical activities for stimulating muscles to estimate human intention, and further control the exoskeleton to provide assistance. There are many advantages of controlling with sEMG. Firstly, the time lag between the onset of muscle movement and that of the exoskeleton assistive motion can be drastically reduced because of the avoidance of electromechanical delay (EMD) [97] which is in favor of forming a real-time neuro-feedback loop [98], and further enhance motor learning according to the neuroplasticity [99]. Secondly, for those with muscle weakness (e.g., patients with incomplete SCI or hemiparetic stroke), motor intention can still be read through the residual sEMG signal. Thirdly, comparing with interaction force, sEMG can be used to predict voluntary joint torque without overcoming limb's inertia and gravity. Fourthly, continuous mapping to joint torque, joint angle, etc. can be implemented by this type of neural signal.

However, there are also disadvantages of sEMG-based control. Firstly, from the perspective of EMG generation, the redundancy of muscle activation solution induces complexity of EMG signal decoding. Secondly, extra complexity was added by confounding factors from different conditions of capturing the sEMG signal, including electrode shift, limb position, contraction intensity, muscle fatigue, time varying, etc. [100], [101]. Thirdly, due to the lack of robustness of sEMG, to date, exoskeleton controlled by solely sEMG input is still unsafe for assisting patients with motor weakness in daily life.

The emergence of human machine interface using sEMG signal dates back to 1970s [102]. Afterwards, sEMG have been extensively applied to prosthesis [103], teleoperation [104], rehabilitation robots [105] etc. Over the decades of development, the sEMG-based control can be divided into the sEMG signal decoding part and the control part, as shown in Fig.4.

The simplest approach is On-Off Control, which relies on pattern recognition to separate human intention into a several classes [106], [107]. The predefined trajectory is replayed when a class is detected. Additional to discrete classes, the decoding process can also map the sEMG signal into continuous output, e.g., human voluntary joint torque. This can be done by three alternative methods: 1) proportional estimation that the predicted joint torque is computed by multiplying a gain to a single channel of filtered sEMG signal [105], [108]; 2) non-linear model that used relatively complicated methods (e.g. machine learning [109] or energy kernel method [110], etc.) to perform the mapping; 3) musculoskeletal model proposed by Hill [111] or other modifications [112], [113] that estimate joint torque upon biological understanding of internal dynamics of human limb [114], [115]. After the continuous torque mapping, a wide range of controllers can be applied to provide assistance. For example, proportional control is the simplest way that the assistive torque is proportional to the human joint torque [108], [116]. Impedance or admittance controller takes the estimated human joint torque as input to reshape the apparent dynamics of the exoskeleton joint to be assistive [117]. It has been covered in the Admittance Shaping chapter. Dynamic-model-based control mainly uses dynamic models adopted from humanoid robotics [118], [119], on which assistive torque calculation was based [120]. Other uncommon method including ambulation speed regulation based on sEMG signal [121], synergy-based control [122], etc.

G. EEG-BASED CONTROL

1) BRIEF OUTLINE

- 1) Purpose: control the LLE according to human intent decoded from electroencephalography signal.
- 2) Concept: various control method based on human intent decoding from signal of brain activities.
- 3) Advantages: direct volitional control; wearers with severe paralysis can still command the LLE; potential of decoding rich information from EEG.

EEG-based Control is manipulating the LLE according to the command from brain-machine-interface (BMI) with electroencephalography (EEG) input. Unlike other brain signal such as ECoG [123], EEG utilizes non-invasive electrodes and has a global view of the brain signal. The term BMI is coined by prof. Miguel Nicolelis, who has led the Walk-Again project that showcased the EEG-controlled exoskeleton in the 2014 Brazil World Cup. Similar to EMG, EEG is also a biological signal generated from human body. The current EMG-based control can perform direct neural control supported by prior knowledge on continuous kinematic information decoding such as musculoskeletal model. Yet most of the current EEG-based exoskeleton controller still have to resort to pattern recognition to decipher the brain signal into discrete classes. The result is that the exoskeleton controller has to provide a set of command based on merely the abstraction of intent. Therefore, how to decode the human intent from the EEG signal and how to control the exoskeleton based on the output of the BMI become two major challenges of EEG-based control strategy.

The general structure of EEG-based controller is shown in Fig.5. Firstly, the BMI captures brain signal to estimate human intent, which is then output as intent abstraction. Secondly, motor control algorithms generate command signals to the exoskeleton to provide assistive torque on the human limbs. And finally, the sensorimotor feedback to the human closes the loop by enabling the wearer to actively regulate the brain signal in order to better receive assistance.

The signals of the brain are essentially generated from neurons. Intraparenchymal electrodes can detect local field potentials deep in the brain. Electrocorticogram (ECoG) captures signal from under the skull but not penetrating the brain. It has been reported that a patient with tetraplegia was able to control a full body exoskeleton up to eight directions using BCI input from implanted ECoG recorders [123]. While electroencephalogram (EEG) utilized non-invasive

electrodes placed outside the scalp, hence it has a global view of the brain signal. This review focus on the EEG because its non-invasion has allowed more extensive usage on not only exoskeleton [124], but also other assistive devices [125].

In real-time EEG signal processing, two types of features are commonly used in BCI. One is endogenous signal that is spontaneous generated by the user, such as ERD [126]. Another is exogenous signal evoked by external stimulus, such as steady state visual evoked potentials (SSVEP) [127] and P300 [128]. Afterwards, decoding algorithms translate these features into human intent estimation. Except a few pilot studies that applied continuous decoding [129], [130], most of the current human intent estimation still utilized discrete classifiers [124].

Another challenge is how to design a controller which, based on only the intent abstraction input, can assist ambulation more naturally or even can be treated as the substitution for the combination of spinal cord and musculoskeletal system. The most frequently used control strategy is trajectory tracking with mechanical balance support [123], [131], [132] or with built-in balance maintaining mechanism [133]. Assist-as-needed strategy was reported as well [126].

Moreover, the sensorimotor feedback is provided to the wearer simultaneously. Thanks to this feedback, not only the machine would make adjustments, but also the wearer would adaptively learn how to moderate brain signals in order to maintain the proper dialogue with the exoskeleton. This was termed as the “two-learner system” by Millán [134]. Because the exoskeleton aims at assisting patients whose corticospinal connection or descending tracts to the muscles are cut due to lesion, the future brain-controlled exoskeleton should function as the substitution for the spinal cord and the musculoskeletal system, so that the wearers can control the human-machine system using the same neural signal to control their intact limb.

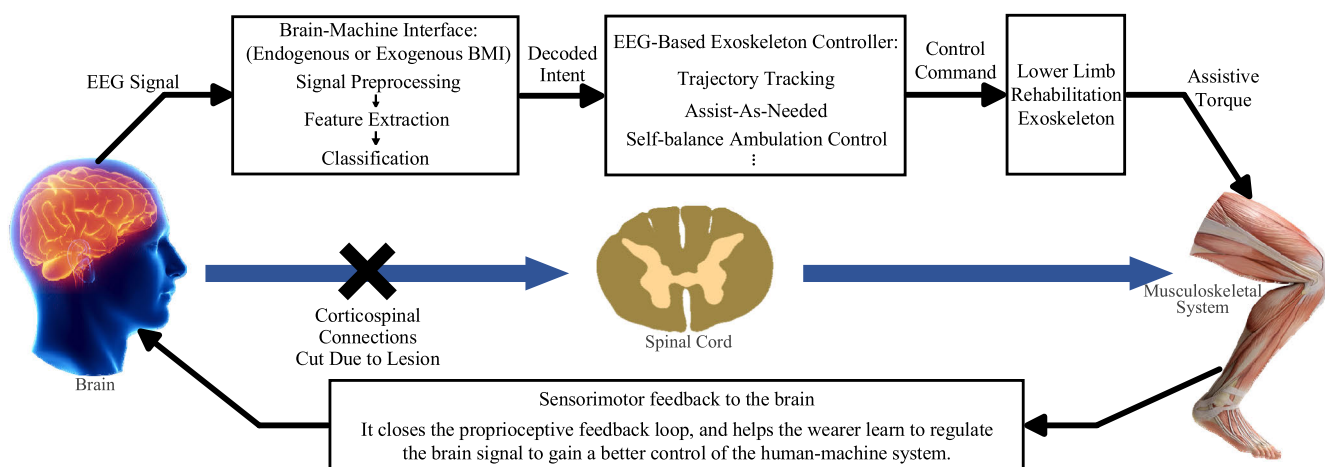


FIGURE 5. Structure of EEG-Based Control. When the internal neural pathway is cut due to lesion, the exoskeleton helps to establish an external neural pathway so that the proprioceptive feedback loop is restored.

H. CONTROL OF HYBRID EXOSKELETONS

1) BRIEF OUTLINE

- 1) Purpose: generate walking gait by controlling robotic actuators and functional electrical stimulation at the same time.
- 2) Concept: the require joint torque for walking is contributed by both robotic actuators and muscles.
- 3) Advantages: improve cardiorespiratory fitness; reanimate muscle function significantly; lighter exoskeletons are needed due to muscle torque contribution.

Hybrid exoskeleton is a kind of rehabilitation devices that combines functional electrical stimulation (FES) with robotic exoskeletons [135]. Control of lower limb hybrid exoskeletons requires modulating torque generated by muscle stimulation and by robotic actuation to achieve a desired walking gait. It was believed to be more beneficial than using FES or robotic assistance only [136]. For example, weight of the robotic actuators in LLE can be reduced due to the significant torque contribution of muscles. Also, regular FES-induced muscle recruitment will facilitate cardiorespiratory fitness enhancement.

As a special device that controls both human and robot, hybrid exoskeletons can be categorized according to whether the robotic actuation is semi-active or fully active, and whether the FES is in open-loop or closed-loop control [137]. Semi-active robotic actuation only dissipates or stores kinetic energy created by muscle stimulation when being controlled [138], [139]. Instead, fully active robotic actuation can compensate or resist muscle torque to perform a desired motion [140], [141]. Open-loop control of FES replays a predetermined pattern of stimulation triggered by FSM [142], [143]. Instead, Closed-loop control of FES relies on indirect measurement of muscle performance to modulate the stimulation in real time [144], [145]. In the spectrum of hybrid exoskeletons, the ones with fully active robotic actuation and closed-loop FES control have been the focus of research in recent years. However, three challenges must be addressed for these devices.

The first challenge is the difficulty of obtaining muscle performance for controlling FES in closed loop. Mostly, indirect measurements are applied. For example, Ha *et al.* used estimated muscle torque profile in one step – computed by subtracting motor torque from nominal torque – as semi-closed-loop feedback signal to shape the FES in the next step [146]. Interaction torque is another frequently used feedback that some FES controllers sought to minimize the interaction torque while the motors ensured a certain reference trajectory was followed [137], [147]. Some other literature employed FES control scheme that based solely on joint position feedback [140], [145].

The second challenge is the complex muscle activation dynamics, including electromechanical delay (EMD), muscle fatigue, nonlinear and time-varying dynamics model, and parameter uncertainties associated with muscle physiology, etc. [148]. Recent literature has investigated how

to design control based on musculoskeletal modeling with stability proof [149]–[151]. However, most of these works were experimented in sitting posture. Generally, activation dynamics were not explicitly modeled in tasks of assisting daily life activities. But instead, adaptive control approaches were employed. For example, iterative learning control has been used to assist walking [137] and sit-to-stand task [145]. And adaptive synergy combination was used to compensate the uncertainty of time-varying model in walking [144].

Within the muscle activation dynamics, the quick onset of muscle fatigue induced by FES also contribute prominently to its complexity. It is because of the nondiscriminatory and synchronous stimulation of all muscle fibers, in contrast with recruiting mainly slow-twitch fibers asynchronously in daily voluntary activities [152]. Currently, the goal of muscle fatigue management is to maintain desired muscle torque output in the presence of fatigue by means of intensifying the stimulation, instead of aiming to delay fatigue. For example, del-Ama *et al.* managed to change muscle stimulation configuration if muscle fatigue is detected – 19% drop of torque-time integral in one step [137]. And Sharma *et al.* scaled the desired muscle activation value by the inverse of normalized fatigue estimation to maintain the desired output [153].

The third challenge is actuator redundancy in hybrid exoskeletons. Because at least one flexor, one extensor and one robotic actuator are needed for an active joint, the number of control inputs can be several times of the number of joints. Some literature adopted a muscle-first approach that most of the kinetic energy was injected from muscle, while the motors only provided a short burst of assistance [143]. Some designed a control strategy that can allocate torque contribution between muscles and motors in an arbitrary ratio. Recently, a bio-inspired control strategy – synergy-based control was proposed to address this challenge, which has the advantage of controlling high-dimensional systems by solving low-dimensional problems [154].

2) SYNERGY-BASED CONTROL

a: BRIEF OUTLINE

- 1) Purpose: reduce the dimension of control problems.
- 2) Concept: inspired by a hypothesis of how human controls movement.
- 3) Advantages: solve the problem of actuator redundancy; reduce the computational complexity of control problems.

Synergy-based control is inspired by a hypothesis that the central nervous system controls the overly redundant musculoskeletal system by linearly combining a small number of synergies – the coherent activation of a group of muscles [155]. Despite no solid proof of the existence of muscle synergy [155], [156], this concept has been used in many robotic applications. Systems with redundant actuation, especially hybrid exoskeletons, can take full advantage of the synergy-based control [140], [144], [154], [157].

Typically, the dynamics model of a hybrid exoskeleton is:

$$M\ddot{q} + C\dot{q} + G + f_{pm} + \Gamma_{ext} = \Gamma \quad (10)$$

where $q \in \mathbb{R}^n$ is the joint angle vector, $\Gamma_{ext} \in \mathbb{R}^n$ is the external torque input and unmodeled disturbances, and $\Gamma \in \mathbb{R}^n$ is active joint torque input. Γ can be defined as:

$$\Gamma = B(q, \dot{q}) \cdot \phi(t) \cdot u(t) \quad (11)$$

where $B \in \mathbb{R}^{n \times m}$ matrix maps the m -dimensional torque input to n joints, $\phi \in \mathbb{R}^m$ is a diagonal fatigue matrix (note that the motors never fatigue, hence the corresponding diagonal elements equal 1), and $u \in \mathbb{R}^m$ is the control input vector defined as:

$$u = [u_{m1} \quad u_{m2} \quad \cdots \quad u_{mk} \quad u_{r1} \quad u_{r2} \quad \cdots \quad u_{rl}]^T \quad (12)$$

where u_{m1} to u_{mk} are k muscle activation inputs, and u_{r1} to u_{rl} are l robotic actuator inputs. According to the muscle-synergy hypothesis, the desired control input can be formed by linearly combining synergies with a small error:

$$u_d(t) = W \times c_d(t) + u_{loss} \quad (13)$$

where $W \in \mathbb{R}^{m \times p}$ consists of p synergies, $c_d(t) \in \mathbb{R}^p$ is the time profile of the non-negative coefficients of linear combination, and u_{loss} is a small construction error that accounts for the part where synergies cannot perfectly fit the desired control input. The number of synergies usually satisfy $p < m$, in order to reduce the dimension of the control problem.

III. DISCUSSION

This paper has reviewed the state-of-the-art control strategies for lower limb rehabilitation exoskeletons. Typical papers within each of the eight categories are listed in Table 1. In this section, the control strategies are further discussed in a macroscopic perspective. This is in attempt to draw a big picture on the current state of LLE control development, along with what to expect from the future control design.

A. THE CURRENT STATES OF CONTROL STRATEGIES

Regardless of the purpose of LLEs, three major challenges persist in the control strategy design: human intention detection, motion control algorithm, and control optimization. Solving the first challenge leads to setting up a steady communication pipeline between the LLE and the human. In the forward direction of the pipeline, the machine is considered more intelligent by understanding the user better. In the opposite direction, sensorimotor feedback provided to the human is a foundation of motor learning and rehabilitation. Solving the second challenge leads to more agile human-machine movements that supports ADL or facilitates rehabilitation. And solving the third challenge allows the control strategies to adapt to different individuals and different tasks. Hereby the current states of the control strategy design that address these three challenges are discussed.

1) SENSING TECHNOLOGIES

One of the earliest yet the most widely used approach to obtain human intention is through “buttons”, which is pressed by wearers or doctors nearby to select walking mode. The “buttons” can be in various type, such as joystick in Rex, touch screen in Atalante [12], and joystick plus trigger buttons in Mina V2 [39]. Despite that this human input approach can only be incorporated with FSM or other high level trajectory planning unit, its high efficacy has been proven in Cyathlon that persons with complete lower limb paraplegia could traverse through complex terrain by this input approach [41]. But the efficacy on rehabilitation is still debatable since active lower limb movement intention is not involved in this control.

Joint angle feedback is virtually mandatory for exoskeleton control, especially in regulating the motor current by comparing the commanded and the real joint angle. But in terms of human intention detection, it is often used as detecting the extent to which the user’s limb is deviated from the desired path in an exoskeleton with backdrivable actuator. Thus, the application includes inferencing interaction torque by displacement of the series elastic actuator [158], deducing the virtual field force by joint angle deviation [68], calculating virtual impedance by the current angular velocity [45], etc.

Interaction torque is another frequently used input especially for admittance controller, which can generate real-time trajectory [159] or make trajectory correction according to it [158]. It is also used to reshape the equivalent constraint dynamics into a desired form [73]. But this input approach implies that wearers must first compensate the inertia and gravity of their own limb to apply force on the LLE. Although imposing negative impedance on the apparent dynamics of the exoskeleton is feasible, it has to deal with the stability issue associated with the positive feedback loop [45].

The utilization of sEMG signal includes replaying trajectory after discrete walking phase recognition and continuous direct volitional control. The latter one exemplifies the advantages of using sEMG signal: to estimate the voluntary muscle force produced by human ahead of EMD [116], [160]. This is important because it provides a method to obtain the human input to the whole human-machine system, instead of merely the interaction torque input to the exoskeleton system.

EEG has a great potential in controlling robotic devices. Yet most of the current employments of EEG signal still resort to black box model to classify a short window of EEG signal for selecting which predefined trajectory to replay. Realizing the potential of EEG can be expected from the breakthrough made by Vouge *et al.* [130] that used continuous regression to enable a monkey wearing an exoskeleton to track a cursor on a screen.

Multi-sensor information fusion has a potential to better decode the human intent. Fusion approach is critical to exploit this potential. The first choice among these approaches is machine learning techniques, e.g., RBF neural network for predicting voluntary joint torque using sEMG and joint

TABLE 1. Summarization of typical papers within each control strategies.

Control Strategy	literature	Target subject / testing subject	Actuated Joint(s)	Actuator	Feedback signal	keywords of control architecture
Trajectory tracking	Griffin et al. [39] Neuhaus [185]	paraplegic / one with paraplegia	hip f/e, knee f/e, ankle d/p	custom linear linkage actuators (Mina-V2 Exoskeleton)	not specified	Detailed offline trajectory planning; Distributed joint-level position tracking control
	Schrade et al. [186]	paraplegic / two with paraplegia	hip f/e, knee f/e	Maxon EC90 for hip, variable stiffness actuator for knee (constructed also by EC90)	angle of hip motor, lever motor, and pretension motor, ground contact	High-level controller for online planning knee stiffness profile and trajectory; Distributed low-level position tracking and stiffness tracking control
	Choi et al. [41]	paraplegic / one with paraplegia	hip f/e, knee f/e	brushless DC motor (Maxon EC22)	trunk inclination, joint angle of hip and knee, ground contact, gait phase	Trajectory generation of Forward Inflection Walking (FIW) method; PID control with feedforward gravity compensation; online risk assessment
	Chen et al. [168]	paraplegic / one healthy	hip f/e, knee f/e	DC motors (Maxon RE40)	hip and knee joints angle and angular velocity, orientation of crutches and trunk, ground reaction force	Offline nominal trajectories obtained by motion capture system; Online trajectory regulation; PD controller for trajectory tracking.
	Cardona et al. [163]	patients with impaired mobility / four with multiple sclerosis	hip f/e, hip a/a, knee f/e	Maxon EC90 Flat, Harmonic Drive Cobalt Line 17, 100 CPM	hip and knee joints angle and angular velocity for adaptive PD controller, sEMG, IMU data, and robot joint angle for high level controller	Trajectory generated by on-board musculoskeletal simulator with multi-sensor-data to adapt to the situation of patients; PD control with adaptive law designed by Lyapunov function
Admittance Shaping	Nagarajan et al. [45]	people who need locomotion assistance / two healthy	hip f/e	Honda Stride Management Assist (SMA)	interaction torque, joint position, velocity, and acceleration	Impedance controller in positive feedback loop reshaped the admittance of the human-machine system; A low-pass filter on the acceleration signal for increasing the stability margin in the presence of positive feedback loop introduced by negative virtual impedance;
	Huo et al. [54]	people with partial locomotion ability / four healthy	knee f/e	DC motor (Maxon) reduction ratio: 264:1	knee joint angle, velocity	Nonlinear disturbance observer for estimating human voluntary force; The human-machine system admittance was shaped to a desired spring damper model; SMC for tracking the output of this desired model
	Tu et al. [50]	people with partial locomotion ability / Three healthy	hip f/e, knee f/e	DC motor (Maxon EC90) reduction ratio: 160:1	joint angle of knee and hip, interaction torque at thigh and shank	Disturbance observer based on fully-actuated model of the human-machine coupled system for estimating the muscle voluntary force; A spring-damper like virtual admittance with adaptive parameters; Adaptive SMC for position tracking
	Zhuang et al. [52]	people who need ankle motor rehabilitation / eight healthy	ankle d/p	direct-drive brushless AC servo motor (DM1B-045G, Yokogawa, Japan)	EMG signal, ankle joint angle	EMG signal of tibialis anterior (TA) for estimating the joint torque; Admittance model using the joint torque as input predicted the intended motion without predefined trajectory; An adaptive PD controller for tracking the intended motion
	Peng et al. [53]	people who need knee motor rehabilitation / eight healthy	knee f/e	not specified (iLeg rehabilitation robot)	EMG signal, knee joint angle	A musculoskeletal model considering three muscles for estimating the voluntary knee joint torque; Virtual admittance for obtaining the desired motion; PID controller for tracking the desired motion
Controllers Utilizing Back-drivability	Murray et al. [66]	hemiparetic / three with hemiparesis	hip f/e, knee f/e	brushless DC motor with backdrivable transmissions (Vanderbilt Exoskeleton)	hip, knee joint angle, velocity	Finite state machine for identifying walking phase; Gravity compensation of the exoskeleton and partial mass of the human leg; Swing assistance when initiating and reversing joint movement; Stance leg reinforcement
	Martinez et al. [68] (Virtual-Field-Based Control)	hemiparetic / five healthy	hip f/e, knee f/e	DC motors (Indego Exo, commercially available)	hip, knee joint angle, velocity	Only swing assistance is provided; FSM for identifying walking phase; Torque field (resembling artificial potential field) that pulls the leg normal to the path
	Martinez et al. [69] (Virtual-Field-Based Control)	hemiparetic / five healthy	hip f/e, knee f/e	DC motors (Indego Exo, commercially available)	hip, knee joint angle, velocity	Swing assistance only; FSM; Flow-field-based controller that offers both guidance and assistance and combines them into one component
	Martinez et al. [67] (Virtual-Field-Based Control)	hemiparetic / two with hemiparesis, one with spastic paraplegia	knee f/e	brushless DC motor (Maxon EC-52i)	hip, knee angle and velocity, ground reaction force	FSM (for both swing and stance phase assistance); Single joint actuation; Flow-field-based controller provided appropriate assistance to joints of s-DOA in a m-DOF system
	Lv et al. [71], [72] (Energy Shaping)	people with (partial) locomotion ability / simulation only	knee f/e, ankle d/p	/	knee and ankle joint angle	The control law was deduced from matching the equivalent constrained dynamics (ECD) before and after energy shaping; Only the potential energy of the actuated joints was shaped to comply with the matching condition.

TABLE 1. (Continued.) Summarization of typical papers within each control strategies.

Control Strategy	literature	Target subject / testing subject	Actuated Joint(s)	Actuator	Feedback signal	keywords of control architecture
Controllers Utilizing Back-drivability	Lv et al. [73], [74] (Energy Shaping)	people with (partial) locomotion ability / one healthy	knee f/e, ankle d/p	PMSM with 43,71:1 transmission (TPM-004X, Wittenstein & 8MGT-720, Gates Industry)	knee and ankle joint angle, event of heel contact, flat foot or toe contact, interaction force	The control law was deduced from matching the ECD before and after energy shaping; Both the inertia energy and potential energy of the actuated joints were reshaped; Yet the controller of total energy shaping differs with different contact phases.
	Lin et al. [75] (Energy Shaping)	people with (partial) locomotion ability / simulation only	knee f/e, ankle d/p	/	knee and ankle joint angle	The contact-phase-invariant control law was deduced from matching the ECD before and after energy shaping; Total energy shaping was applied to not only actuated joints but also unactuated joints.
	Lin et al. [170] (Energy Shaping)	people with (partial) locomotion ability / one healthy	knee f/e, ankle d/p	200W Emoteq frameless brushless DC motors with custom 24:1 transmission	knee and ankle joint angle, ground reaction force	IDA-PBC method adopted from compass gait bipedal robots was used to reshape the Gravitational term and Centrifugal/Coriolis term; Optimization techniques fitted the shaped terms to natural walking gait.
Virtual Constraint	Agrawal et al. [84]	paraplegic / simulation only	hip f/e a/a r/c; knee f/e; ankle d/p a/a	/	all joint angle and velocity, forward hip velocity, torso incline angle	Offline trajectory optimization for defining virtual constraint; Input/output feedback linearization controller
	Harib et al. [12], [83]	paraplegic / three with paraplegia	hip f/e a/a r/c; knee f/e; ankle d/p a/a	brushless DC motor	angle and velocity of all joints, forward hip velocity	Offline trajectory optimization for defining virtual constraint; Input/output feedback linearization controller in simulation to obtain nominal trajectory; Ordinary trajectory tracking in practical control
	Campbell et al. [187]	hemiparetic / simulation only	hip f/e, knee f/e, ankle d/p	/	all joint angle and velocity, forward hip velocity, CoM horizontal velocity	Virtual constraint approach is deactivated in the deadzone located around desired trajectory to achieved ANN control
	Tucker et al. [172]	people with paraplegia / three healthy	hip f/e a/a r/c; knee f/e; ankle d/p a/a	brushless DC motor (Atalante exoskeleton)	all joint angle and velocity, ground and chair contact force	An proposed coactive learning approach that makes query to users before each update finds the gait trajectory that maximize the user utility; Virtual constraint and input/output linearization controller tracks the optimized trajectory.
	Mungai et al. [188]	people with paraplegia / simulation only	hip f/e a/a r/c; knee f/e; ankle d/p a/a	/	all joint angle and velocity, ground and chair contact force	Quadratic programming and input/output linearization was combined to compute the optimal torque output for over-actuated system rendered by numerous contact constraint in the sit-to-stand process.
Oscillator-Based Control	Ronsse et al. [87]	people with (partial) locomotion ability / nine healthy	hip f/e	SEA (LOPES exoskeleton)	hip joint angle	Joint angle predictor using a pool of phase oscillators and a kernel-based non-linear filter; Force field formed by phase lead and proportional control
	Xue et al. [93]	people with (partial) locomotion ability / six healthy	hip f/e	SEA (harmonic FHA-14C actuator, FHAE exoskeleton)	hip angular velocity	An improved oscillator (adding adaptive parameters and right/left leg coordination term to the Hopf oscillator) as phase locker; Discrete transition to different walking states; Direct torque control based on offline nominal torque database
	Gams et al. [88]	people with (partial) locomotion ability / seven healthy	knee f/e	DC motor (Maxon RE50)	knee joint angle	Adaptive phase oscillator combining a simple phase oscillator and adaptive Fourier series; Torque output was calculated by regulating the nominal torque database
	Zhang et al. [89]	people with locomotion ability / twelve healthy	ankle d/p	brushless DC motor (Maxon EC45)	ankle joint angle, ankle interaction torque	Gait phase synchronization by adaptive frequency oscillator (AFO) and phase correction; Kernel-based NLF was used to predict the real-time interaction force; Ankle actuation provided force that is proportional to the predicted interaction force
	Seo et al. [90]	people with (partial) locomotion ability / two healthy	hip f/e, a/a; knee f/e	electrical motors with maximum torque of 30 Nm	walking speed, foot-to-foot distance, discrete walking environment class	A particularly shaped adaptive oscillator with foot-to-foot distance input for estimating gait phase; Torque output that was based on gait phase and offline trajectory function, and was regulated by walking speed and environment class
	Aguirre-Ollinger et al. [189]	hemiparetic (with only one side of paretic knee) / eight healthy	knee f/e	variable-structure SEA (with two switchable spring stiffness level)	thigh and knee joint angle, position of SEA internal components	Adaptive oscillator for continuously estimating gait phase; Reference joint torque as a bell-shape function of gait phase; Three component (model-based feedforward control + FPRE-based feedback control + disturbance observer) for SEA force tracking

TABLE 1. (Continued.) Summarization of typical papers within each control strategies.

Control Strategy	literature	Target subject / testing subject	Actuated Joint(s)	Actuator	Feedback signal	keywords of control architecture
EMG-Based Control	Kawamoto et al. [190]	people with gait disorder / one healthy	hip f/e; knee f/e	DC-motor with harmonic drive	sEMG, ground reaction force (for FSM)	Finite state machine (FSM) for different walking phases, where the phase shift timing was depended on the ground contact detection; The assistive torque was regulated by maintaining the sEMG-related ratio of assistance.
	Ao et al. [191]	patients with motor disorders / eight healthy	ankle d/p	a direct drive brushless AC servo motor	sEMG, ankle joint angle	Two methods were compared: 1) calibrated hill-type musculoskeletal model, 2) proportional model calibrated by maximum voluntary contraction; Both used constant gain to output the assistive torque
	Lyu et al. [192]	patients who need motor recovery / six healthy	knee f/e	Brushless DC motor (Maxon EC 90)	sEMG, ankle joint angle	Kalman filtered sEMG signal; The desired knee joint angle was set proportional to the filtered sEMG signal; PID trajectory tracking.
	Grazi et al. [122]	patients with muscle weakness / eight healthy	hip f/e	SEA	sEMG, vertical ground reaction force	Gait phase estimated by adaptive oscillator; Within the 20% to 60% of the gait phase, the sEMG signal of the ankle-driving muscle was filtered and multiplied by a constant gain to obtain the desired hip torque output; The actual torque imposed on the hip was delayed by certain phase.
	Durandau et al. [108]	patients who need rehabilitation / four healthy, one with incomplete SCI, two with hemiparetic stroke	knee f/e; ankle d/p	non-back-drivable motors (Maxon)	sEMG, knee and ankle joint angle	sEMG filtering; Musculoskeletal model for human joint torque estimation; Desired assistive torque that proportional to human torque; Torque control loop
	Young et al. [193]	not specified / ten healthy	hip f/e	artificial pneumatic muscle	method 1: sEMG method 2: heel strike detection	Compared two methods: 1) sEMG proportional control (PMA torque output was proportional to filtered sEMG), 2) mechanical intrinsic controller (tracking predefined torque profile)
	Xia et al. [194]	patients who need rehabilitation / two healthy	hip f/e; knee f/e	DC motor (SIAT lower-limb exoskeleton)	hip and knee joint angle and velocity, sEMG	BP-NN estimates voluntary joint torque with sEMG and joint angle input; Model-based control algorithm with RBF-NN fitting unknown function compensates human voluntary joint torque to track the desired trajectory.
EEG-Based Control	Do et al. [195]	patients with paraplegia or tetraplegia / one healthy, one with paraplegia	hip f/e, knee f/e	RoGO Exoskeleton (commercially available)	EEG	Classification for predicting the Walking or Idling motor imagery: (PSD feature extraction, CPCA-AIDA dimensionality reduction, and linear Bayesian classifier); In the walking state, the predefined trajectory was tracked.
	Kwak et al. [196]	patients with paraplegia or tetraplegia / 11 healthy	hip f/e, knee f/e, ankle d/p	REX Exoskeleton (REX Bionics Ltd.)	EEG	Five visual stimuluses corresponding to five exoskeleton states; Classification: (2s windows signal, CCA method for extracting features KNN classifier); The exoskeleton will walk half a step after one single intention was detected.
	Wang et al. [131]	not specified / four healthy	hip f/e, knee f/e	DC motor (SIAT lower-limb exoskeleton)	EEG	MI-driven BMI (CSP for feature extraction, SVM as classifier) and SSVEP-driven BMI (CCA for feature extraction, SVM as classifier) were compared for classifying three classes: walking, sitting down, and standing up; Trajectory tracking for each class.
	Gordleeva et al. [161]	patients with paraplegia or tetraplegia / eight healthy	hip f/e, knee f/e	DC motor	EEG, sEMG	HMI based on EEG + sEMG allows detecting left or right leg motor imagery or motor execution to control the ipsilateral leg movement.
	López-Larraz et al. [126]	patients with incomplete SCI / three healthy, and four with SCI	hip f/e, knee f/e, ankle d/p	DC motor	EEG, joint angle, interaction torque	Classification for Movement attempt or Rest state: (ERD / MRCP for feature extraction, SPA as classifier); Assist-as-needed strategy with predefined trajectory and interaction force input to move one gait cycle after detecting the Movement attempt.
	Lee et al. [197]	patients with tetraplegia / 5 healthy	hip f/e, knee f/e, ankle d/p	REX Exoskeleton (REX Bionics Ltd.)	EEG	Three states (walking, turning left, or turning right) was classified by a cascaded binary (Move/Relax) classifier; These states would be then executed by Rex; Obstacle avoidance was performed by Kinect sensor.

TABLE 1. (Continued.) Summarization of typical papers within each control strategies.

Control Strategy	literature	Target subject / testing subject	Actuated Joint(s)	Actuator	Feedback signal	keywords of control architecture
Control of Hybrid Exoskeletons	Ha et al. [146]	people with paraplegia / three with paraplegia	hip f/e, knee f/e	brushless DC motor with backdrivable transmissions (Vanderbilt Exoskeleton)	all joint angle, motor torque output in the preceding step	Motor control: predefined trajectory & PD control; Muscle control: semi-closed-loop control with feedback of motor torque output in the preceding step
	del-Ama et al. [137]	people with paraplegia / four healthy	hip f/e	DC motor (Maxon), 100:1 gear (Harmonic Drive)	all joint angle, interaction force, heel strike timing (for FSM)	Motor control: torque field with stiffness and damping term; Muscle control: PID for stimulating knee extensor muscle, and iterative learning control for stimulating knee flexor muscle
	Nandor et al. [143]	people with paraplegia / two with spinal cord injury	hip f/e, knee f/e	DC motor (Maxon EC45), 100:1 backdrivable transmission	all joint angle and velocity, motor current, heel strike timing (for FSM)	Mode-1: open-loop FES control, motors provide resistance compensation torque only; Mode-2: open-loop FES control, motors provide a short burst of assistance torque in each step
	Molazadeh et al. [145]	people with paraplegia / four healthy, one with complete spinal cord injury	hip f/e, knee f/e	DC servo motors (Harmonic Drive) for hip, DC brushless motor (Maxon) for knee, both with 100:1 transmission	all joint angle and velocity	Offline optimization generates time-dependent trajectory for right knee, and time-independent virtual constraint for other joints; Iterative learning control automatically adapts to the subject's musculoskeletal model and other uncertainties; FES-motor allocation ratio can be arbitrary switched
	Alibeji et al. [144] (synergy-based control)	people with paraplegia / one healthy, one with incomplete spinal cord injury	hip f/e, knee f/e	DC motor (Maxon EC90), Harmonic Drive transmission	all joint angle and velocity, activation level of muscles and motors	Two offline optimizations: one for computing muscle synergies using dynamic postures, another for combining these synergies into gait motions; PID in series with dynamic surface control for being robust to muscle fatigue, muscle electromechanical delay, and disturbances.

Abbreviation list: f/e: flexion/extension; a/a: abduction/adduction; r/c: rotation/circumduction; d/p: dorsiflexion/plantarflexion; SMC: sliding mode control; PMSM: permanent magnet synchronous motor; FSM: finite state machine; ANN: assist-as-needed; SEA: series elastic actuator; CoM: center of mass; PMA: pneumatic muscle actuator; PSD: power spectral densities; CPCA: classwise principal component analysis; AIDA: approximate information discriminant analysis; CCA: canonical correlation analysis; KNN: k nearest neighbor; CSP: common spatial patterns; SVM: support vector machine

angle [109], LDA for classifying human intent using sEMG and EEG [161], and CNN for recognizing gait phase with plantar pressure and IMU acceleration data [162]. The second is on-board musculoskeletal simulator, which was first proposed in [163] to estimate the wearer's kinetic gait profile using sensor data from both human and robot. The third is to explicitly put multiple sensor inputs into the control law. For instance, [73] used joint angles and interaction force to complete the equation of equivalent constrained dynamics, and ground contact force to switch to dynamics of different walking phase.

2) MOTION CONTROL ALGORITHMS

Which particular motion control algorithm to be adopted affects by many factors, such as 1) the actuator is backdrivable or not, 2) whether passive trajectory following or active rehabilitation training is required, and 3) whether involving dynamics model is necessarily to improve torque output accuracy. The following passages discuss which is the optimal type of motion control algorithm in different scenarios.

Generally, the control based on predefined trajectory is enough versatile to assist ADL [39]. This type of control relies on a high-level FSM to select which predefined trajectory is to be replayed. The FSM can take classification result of EEG or EMG as input, or employ buttons input. However, numerous parameters should be tuned for each individual, including different walking phase parameters in different terrain.

One solution is introducing human intention input that is less abstract, e.g., gait completion percentage estimated by oscillator, interaction torque, and human voluntary joint torque estimated by EMG. These inputs can lead to oscillator-based control [87], interaction-torque-driven admittance shaping [45], [59], and EMG-driven admittance shaping [52], respectively. These are more dexterous in assisting human locomotion. Furthermore, these control strategies results in active rehabilitation training. It has been reported that usage of active training devices such as EMG-driven HAL in patients with SCI led to muscle hypertrophy, nerve regeneration, and neural system reorganization [164]–[166]. Similar outcome was shown for stroke patients that rehabilitation result equivalent to traditional therapy and even bonus effect for sub-acute patients were reported [167]. Another solution is replacing the predefined trajectories with optimized ones, which is covered in discussion topic “optimization techniques”.

Whether the actuator is backdrivable also have a significant impact on the control algorithm design. For non-backdrivable motors, especially that with high transmission ratio, usually the corresponding motion controller is in kinematic control mode, i.e., regulating the joint angle or joint velocity of the actuator. The kinematic approach can be in the form of plain trajectory tracking [168], admittance control [54], some of the biological- signal-based control [121], and so on. The controller for executing the kinematic command can be simple PID [41], or with some sophisticated method such

as model-based control, which directly regulate torque output by input-output linearization controller in underactuated model [12], or by feedback linearization controller in fully-actuated model [50].

If the exoskeleton makes use of backdrivable actuator, e.g., pneumatic muscle, SEA, and PMSM with low transmission ratio, then its association with intelligent control would provide more flexible human-machine movement. One of the important features of these motion controllers is to use joint angle deviation to estimate human intention and to further make adjustment. This feature leads to, for example, virtual-field-based control which adjust the exoskeleton torque output by measuring joint angle deviation [68], or energy shaping which reshapes the dynamics equation [74].

Involvement of dynamics model or not is also a key factor in motion control algorithm design. There are three types of frequently used dynamics model for LLE: 1) simple one DoF mass-spring-damper model [169], 2) fully-actuated dynamics model [50], [51], and 3) floating-base hybrid dynamics model [12], [74]. The first one can be used to characterize the SEA or describe the machine side of the exoskeleton. For this manner of modeling, admittance shaping can reshape the parameters within the model into a desired form. In terms of fully-actuated model, usually the pelvis is modelled as the fixed base. And the feedback linearization techniques can be applied in single support phase to calculate the required torque output. Regarding the floating base hybrid dynamic model, two available corresponding controllers are: input-output feedback linearization controller and energy shaping. The former requires explicitly defined trajectory (i.e., virtual constraint). While the latter operates without specifying trajectory and allows for free human-machine movement in various direction and velocity.

3) OPTIMIZATION TECHNIQUES

Recent years have witnessed increasing application of optimization techniques in control of LLEs in order to better meet different control objectives, which can be 1) quick adaptation to different user' condition or preference [170]–[172], 2) minimizing human joint torque or metabolic cost [173], [174], and 3) faster comfortable walking [175], etc. These techniques have been employed to perform parameter optimization [171], [173], [176], trajectory optimization [12], [172], [174], [175], [177], and control law optimization (optimal control) [178]–[180].

Parameter optimization is to find the optimal set of parameters within the designed control algorithm, instead of heuristically tuning it. However, the fact that usually the cost function can only be updated after completing a few gait cycles makes the cost function a black box, whose derivatives are impossible to compute. Therefore, derivative-free optimization techniques can be applied. For example, the performance of Bayesian Optimization and Evolution Strategy were evaluated respectively in [173] to find the best set of energy shaping factors that minimize human joint torque exerted. Moreover, reinforcement learning technique SARSA

was employed in [176] to adjust the parameters in admittance controller for the purpose of encouraging patient force input in active rehabilitation training.

Trajectory optimization is to plan an optimal motion profile for the subsequent tracking controller. In the field of LLE, the complex hybrid and underactuated dynamics makes solving the optimization problem time-consuming. Thus, often only offline trajectory optimization is employed. For example, direct collocation technique [181] is applied to Atalante exoskeleton, considering friction cone for no foot slippage, ZMP for no foot rotation, and proper foot clearance, etc. [12]. This technique has been proven effective and robust, and has also been applied to other sophisticated robots [182]. In [177], a Guided trajectory learning method was first proposed to suit the need for low time complexity of online trajectory planning. Its idea is using deconvolution neural network trained by the database of trajectory optimization to predict the online trajectory. Specially, the trajectory optimization also adapts itself to make sure the neural network is perfectly trained.

Human in the loop is a special approach of trajectory optimization for LLEs. Tucker et al. has proposed a COSPAR algorithm in this approach [172], which finds the trajectory parameters that the user most prefer. Besides, the team led by Prof. Steve Collins has built an idealized exoskeleton emulator using offboard actuators to investigate what is the best control strategy for future LLEs [183]. They found the best assistive torque profile with minimal metabolic cost in [174], and that with faster self-selected walking speed in [175]. Interestingly, they concluded that the benefits of LLEs originate from the changes in the wearer to adapt to the new walking pattern.

Optimal control that directly incorporate the optimization techniques into the feedback control law is still challenging for LLEs. Promising advances have been made recently. For example, it was investigated how to perform trajectory tracking control using reinforcement learning in simulation [184], and in human subject test [178], and how to perform assist-as-needed control [179], etc.

B. FUTURE EXPECTATIONS

The exoskeleton is playing an important role in assistance and rehabilitation for persons with motor disabilities. However, before vastly deploying LLEs into daily life, three requirements should be met: empowerment, embodiment, and agility.

The first requirement is a basic prerequisite that exoskeletons should empower the wearer with motor disabilities to stand up and walk normally. The future control strategies should solve the balance maintenance issue rather than passively strapping the user with paralysis to a cumbersome exoskeleton which is balanced with large foot. Regarding hemiparetic patients with partial balancing skill, the future LLE should have a high bandwidth and response quickly to the human intention, which is important for the users to voluntarily command the human-machine system to recover balance from unexpected impacts.

In addition to balance, the collective gait should be carefully designed, which should be energy economic and conforming to medical instructions. Afterwards, tracking the desired gait (either defined offline or generated in real-time) may require an accurate dynamics model, in which human-machine coupling, closed chain dynamics during double leg support, and rigorous post-impact mapping should be integrated. It is also expected that the future bio-signal to be precisely decoded for establishing an accurate human-machine dynamics model.

The second requirement for future LLEs is embodiment. Whenever human perform a movement, the neural signal from the brain goes through spinal cord and peripheral nerve to reach the muscle. While the exoskeleton with decent human intention detection provides appropriate assistance to the musculoskeletal system, which produces proprioceptive feedback to the brain to close the human motion control loop. The future LLEs should be predictable enough so that the real proprioceptive feedback accords with the brain's pre-estimation. Because of brain plasticity, this predictability allows the user to assimilate the exoskeleton into their body schema so that wearers can use it not as a tool, but as part of their body.

The future exoskeleton should also meet the requirement of agility. This is for users to swiftly perform complex movements, such as sit/stand transition and stair descending or ascending. Moreover, the ability to traverse through complex terrains and to navigate through moving obstacles is also needed.

IV. CONCLUSION

This paper focuses on the recent developments in the control strategies of lower limb rehabilitation exoskeleton, which are categorized according to their similarities. Technical details within eight different classes are reported. However, the state-of-the-art control strategies are yet to maximize the potential of the modern hardware. It is concluded that future developments of control may benefit from: 1) more precise human intention decoding, which is the foundation of realizing human-robot shared control; 2) smarter core control algorithms that respect human intention and are compatible in various tasks; 3) more accurate human-machine dynamics model; 4) better predictability of the LLE for facilitating embodiment; 5) more intelligent balance assistance that lean not on non-backdrivable actuators. Before meeting the ultimate goal of empowerment, embodiment, and agility, there is still a long way ahead.

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