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# Recent Development of Mechanisms and Control Strategies for Robot-assisted Lower Limb Rehabilitation

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### *Abstract*

Robot-assisted rehabilitation and therapy has become more and more frequently used to help the elderly, disabled patients or movement disorders to perform exercise and training. The field of robot-assisted lower limb rehabilitation has rapidly evolved in the last decade. This article presents a review on the most recent progress (from year 2001 to 2014) of mechanisms, training modes and control strategies for lower limb rehabilitation robots. Special attention is paid to the adaptive robot control methods considering hybrid data fusion and patient evaluation in robot-assisted passive and active lower limb rehabilitation. The characteristics and clinical outcomes of different training modes and control algorithms in recent studies are analysed and summarized. Research gaps and future directions are also highlighted in this paper to improve the outcome of robot-assisted rehabilitation.

***Keywords***: rehabilitation robot; lower limb; training mode; control method; robot mechanism

## 1 Introduction

According to the data from World Health Organization (WHO), the proportion of world's people over 60 years will be doubled from 11% to 22% between 2000 and 2050. During the same period, the number of elderly people aged over 60 years will increase from 605 million to 2 billion. More than half of the worldwide elderly people live in Asia (54%), followed by Europe (22%) [1]. Many countries have gradually entered the aged society. Meanwhile, there are about 650 million people with disabilities worldwide, accounting for about 10% of the world's total population, where 80% of disabled people live in developing countries [2]. The report "2013 China Statistical Yearbook of Disabled People" shows that the total number of people with disabilities in China is approximately 37.95 million [3], in which the physically limbs disabled is 15.64 million, occupying 59% of the total disabilities. Among the aged society and increasing disabled population, there will be obvious recession in these people's physiological functions, severely affecting their daily lives.

The rehabilitation and training of elderly, disabled and other movement disorders has become a major social problem to be resolved, however, the conventional manual therapy mainly relies on the therapist's experience, making it difficult to meet the requirements of high-intensity and repetitive training [4]. The number of physiotherapists is severely lacking, and the evaluation methods are mostly subjective, so the treatment effects cannot be guaranteed [5]. In this situation, there is a considerable increase in the needs of advanced rehabilitation devices, which are expected to assist patients to perform training exercise precisely, quantitatively and scientifically [6]. Rehabilitation robotics has become a research field that attracts more and more attentions in the last decade. Applying robots to rehabilitation can not only release physicians from the heavy burden of training

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missions, but also evaluate patients' recovery status by analysing the data recorded in robotic training process. Due to its advantages in terms of accuracy and reliability, rehabilitation robotics is able to provide an efficient approach to improve the recovery outcomes after stroke or surgery.

Nowadays, there have been several published review papers on control strategies of robotic rehabilitation and training. For example, a review on categories of control strategies of all kinds of rehabilitation robots was conducted in [7], however, very few details of mechanisms and control algorithms were given to the lower limb rehabilitation robots. Diaz et al. conducted a comprehensive survey of existing robotic systems for lower limb rehabilitation [8]. This review is quite informative. It covered most current lower limb robots, however, the robotic training modes and control strategies were not emphasized somehow. Kwakkel et al. presented a systematic review on the effects of robot-assisted therapy and mainly focused on the clinical outcomes of different robots [9], in which the detailed discussion of robot control strategies was also included. On the other hand, Hussain et al. provided a review of the treadmill based robotic gait training devices but specifically focused on the control strategies related to treadmill robots [10]. Mohammed et al. reviewed the state of the art of the lower limb wearable robots [11, 12], which mainly focused on actuated exoskeletons and the control strategies in them. Another review concentrating on lower limb exoskeletons and active orthoses was done by Dollar and Herr [13], but it only covered devices that operate in parallel with human legs. In recent years, novel control strategies (such as adaptive control and assist-as-needed control) have been widely used in lower limb rehabilitation robots, but they are not specifically discussed in previous papers. With the emerging human-robot interaction techniques, biofeedback and hybrid control have also become more and more popular in newly developed rehabilitation robots. Although many review papers mentioned that bio-signals based control strategies have been regarded as effective strategies and become a popular research area, however, none of them have investigated or summarized the recent studies on this kind of strategies [14].

This paper gives a review and analysis of mechanisms, training modes and control strategies of lower limb rehabilitation robots, especially the control methods considering hybrid data fusion and adaptive learning laws. It provides an introduction of the most recent development of robot-assisted lower limb rehabilitation, and also summarizes the research gaps and potential future directions. The rest of paper is organized as follows. Section 2 compares different mechanisms of lower limb rehabilitation robots. In Section 3, the robot-assisted training modes for different recovery stages are analysed. Section 4 presents recent development of robotic control strategies, including position control, impedance control, biofeedback control and adaptive control. In Section 5, the research limitations and future directions are discussed and concluded.

## 2 Mechanisms of Lower Limb Rehabilitation Robots

Mechanical design is the basis of robot-assisted rehabilitation system, and should follow a basic principle of keeping its structure simple, lightweight, and easy to control. In recent years, various types of robots have been developed for lower limb rehabilitation. Generally, these robots can be divided into two categories: exoskeleton and end-effector robots [15]. For example, Lokomat [16], BLEEX [17] and LOPES [18, 19] are typical exoskeleton robots, while Rutgers Ankle [20], and Haptic Walker [21] are end-effector robots. According to their mechanisms and rehabilitation principles, exoskeleton robots can be grouped as the treadmill-based devices and the orthosis-based robots, while the end-effector robots have footplates-based and platform-based types. An overview of recent representative robots and their characteristics is demonstrated in Table 1.

***Table 1** Overview of recent lower limb rehabilitation robots*

| Groups | Devices | Institutions/researchers | Actuated DOF* | Characteristics |
|---|---|---|---|---|
| Treadmill based exoskeleton robots | Lokomat [16] | Hocoma, Switzerland | Two-leg DOFs for treadmill walking | Treadmill training with body weight support system; it provides powered assistance at the hip and knee by strapping patient's legs. |
| | Lokohelp [22] | Woodway & Lokohelp Group, Germany | Two-leg DOFs for walking with levers on treadmill | It can be placed on a treadmill with weight support mechanism; it transmits movement of treadmill to levers for patients to track. |
| | LOPES [18, 19] | Veneman et al. from University of Twente, Netherlands | Three rotational DOFs in each leg for walking on treadmill | A leg exoskeleton containing three actuated rotational joints: two at the hip and one at the knee; it can move in parallel with the legs when walking on a treadmill. |
| | ALEX [23] | Banala and Agrawal et al. from University of Delaware, US | Seven DOFs for translations and rotation of a leg | It is a powered leg orthosis with actuators at hip and knee joints; it provides assistance to the patient walking on a treadmill. |
| Leg orthoses and exoskeletons | AAFO [24] | Blaya and Herr from Massachusetts Institute of Technology (MIT) | Two motion DOFs for ankle joint | It is an active ankle-foot orthosis, uses SEA as the actuation; ankle joint was fabricated to fit; allows free motion in sagittal plane. |
| | KAFO [25] | Sawicki and Ferris from University of Michigan, US | Free motion DOFs in sagittal plane for ankle and knee | It is a knee-ankle-foot orthosis; six artificial pneumatic muscles are attached to orthosis to power ankle and knee movements. |
| | HAL [26] | Tsukuba University & Cyberdyne, Japan | Full-body exoskeleton for arms, legs, torso | It is a full-body exoskeleton for rehabilitation and heavy works support; and EMG* signals are used to map patient's intention. |
| | BLEEX [17] [27] | Kazerooni et al. from University of California, US | Seven DOFs for each leg in hip, knee and ankle joints | It is a pair of wearable robotic legs developed to increase the abilities of the wearer, provide power to carry major loads. |
| Foot plates based end-effector devices | Gait Trainer GTI [28] | Reha-Stim, Germany | Two footplates for foot/leg movement | Patient's feet are positioned on footplates with movements are controlled to simulate foot motion during stance and swing. |
| | Haptic Walker [21] | Hesse et al. from Charité University Hospital, Germany | Arbitrary movement DOFs for two feet | It allows simulation of various gait patterns and walking speeds; force/torque sensors are located under each footplate. |
| | G-EO-Systems [29] | Reha Technology AG, Switzerland | Two footplates for walking and climbing DOFs | It is an end-effector gait robot with freely programmable footplates; can be controlled to stimulate walking and climbing stairs. |
| Platform based end-effector robots | Rutgers Ankle [20] | Girone et al. from Rutgers University, US | Six DOFs for ankle and foot based on a Stewart platform | It supplies 6-DOF resistive forces to patient's ankle with virtual reality, and later extended to a dual platform for gait rehabilitation. |
| | ARBOT [30, 31] | Saglia et al. from Istituto Italiano di Tecnologia, Italy | Two ankle DOFs in plantar/dorsiflexion, inversion/eversion | It is a parallel robot for ankle rehabilitation with patient's foot fixed on the moving platform, a customized linear actuator used. |
| | Parallel Ankle robots [32, 33] | Xie et al. from The University of Auckland, New Zealand | Three ankle DOFs provided by 4-axis parallel robot | A 4-link robot driven by DC motor actuators and a 4-axis parallel robot driven by pneumatic muscles designed for ankle rehabilitation. |

### 2.1 Exoskeleton robots for lower limb rehabilitation

#### 1) Treadmill based exoskeleton robots

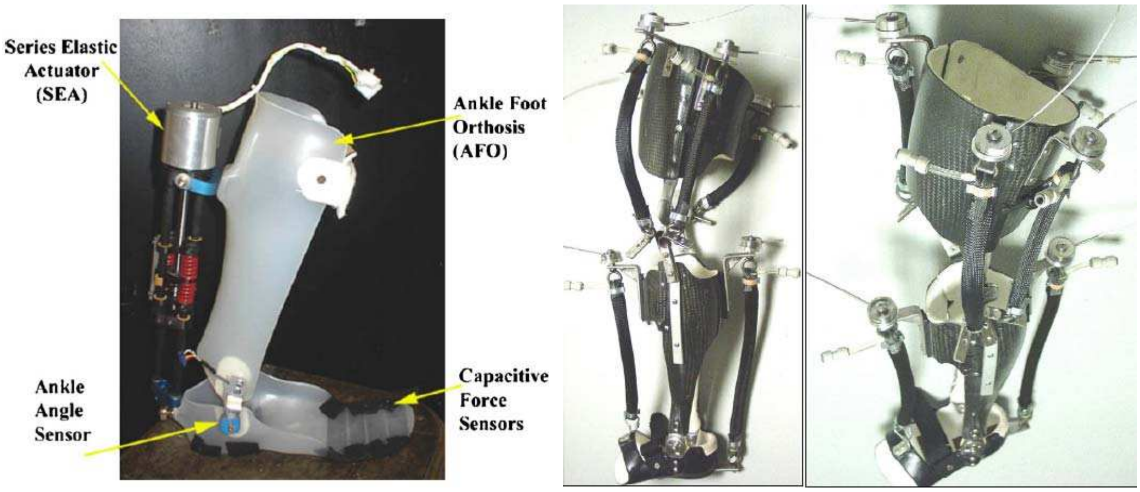
Treadmill based exoskeleton robots usually consists of a body weight support system and a lower limb exoskeleton patients wear while walking on a treadmill frame. The Lokomat, developed by Hocoma (Zurich, Switzerland), is a typical treadmill based exoskeleton with body weight support mechanism (Fig. 1(a)). The patient's legs are strapped into an adjustable frame to provide powered assistance at the hip and knee [34]. The Lokohelp group developed a lower limb rehabilitation robot with structure similar to Lokomat [22]. It transmits the treadmill movement to levers positioned on both sides of the device, so the simulation of gait is achieved by the track of the levers [35]. This robot can assist the patient to perform active training. Another important body-weight supported treadmill robot system is AutoAmbulator (Healthsouth, US), in which robotic arms are strapped to the patient's legs. However, few literatures are reported by using this device. Recently, a new gait training robot LOPES [18] was developed by University of Twente, as shown in Fig. 1(b). It combines a translatable and 2-D-actuated pelvis segment with a leg exoskeleton containing three actuated rotational joints. LOPES can move in parallel with the legs of a person while walking on a treadmill. Researchers from the University of Delaware have developed an Active Leg EXoskeleton (ALEX) [23]. It is a powered leg orthosis with linear actuators at the hip and knee joints, and with a force-field controller developed to provide assistance to the patient during walking [36]. Though treadmill-based robotic devices are potentially beneficial for the patient in terms of energy expenditure reduction, the operation of these robots often requires more than two operators, thus considerable efforts are required. Another common problem existing in these devices is the weight support mechanism, which may limit patient's free movements initiated by themselves.

#### 2) Leg orthoses and exoskeletons

Leg orthoses are actuated wearable exoskeletons that can provide walk power assistance. Blaya and Herr from Massachusetts Institute of Technology developed an Active Ankle-Foot Orthosis (AAFO) (Fig. 2(a)) [24], which is one of the main devices designed for treating a gait pathology known as drop foot. Yet, actuation system and control scheme in this robot need further improvements. The artificial pneumatic muscles may be a good choice for exoskeleton orthoses because of their force-to-weight ratio and intrinsic safety. Sawicki and Ferris at University of Michigan developed a Knee-Ankle-Foot-Orthosis (KAFO) powered by artificial pneumatic muscles, as shown in Fig. 2(b) [25]. It is used for motor rehabilitation to provide flexion and extension torque during human walking. Fleischer et al. from Berlin University of Technology developed a powered orthosis [37], in which intended motions of the subject are evaluated through EMG signals. Hybrid Assistive Limb (HAL) is a full-body exoskeleton developed by Tsukuba University and Cyberdyne for rehabilitation and heavy support [26]. EMG signals are also used in HAL to measure the level of human-robot interaction. However, this technique is quite difficult to achieve for paraplegic patients because of the paralyzed muscles that cannot generate effective EMG signals. Berkley Lower Extremity Exoskeleton (BLEEX) is an exoskeleton developed by University of California to increase the abilities of the wearer in term of both strength and endurance [27]. There are seven DOFs in BLEEX, four of which are actuated by hydraulic actuators. Although the flexible gait rehabilitation can be achieved by these orthotic systems, the shortcomings such as high energy cost also hinder their wide applications. On the other hand, control parameters of the exoskeleton ortheses also need to be frequently adjusted, while the proactive interaction between the robot and user makes the tuning process challenging.

(a) Lokomat [38] (b) LOPES [39]

***Fig. 1.*** *Treadmill-based exoskeleton robots.* (a) is reprinted from [38], with permission from Elsevier. (b) is reprinted from [39], an Open Access article with unrestricted use permission.




(a) AAFO [40] (b)KAFO [25]

***Fig. 2.*** Leg orthoses and exoskeletons. (a) is reprinted from [40], with permission from Elsevier, (b) is is reprinted from [25], an Open Access article with unrestricted use permission.

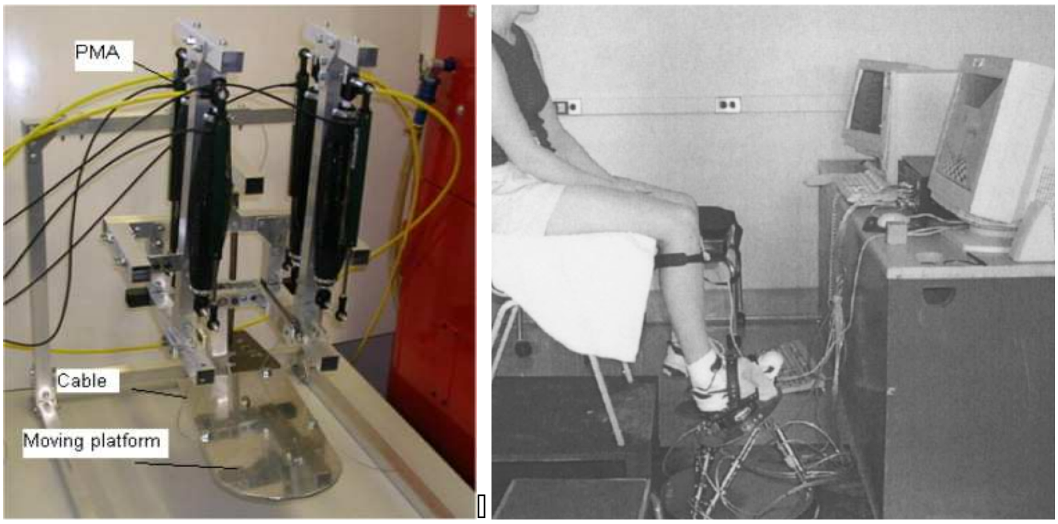
**2.2 End-effector robots for lower limb rehabilitation**

**1) Foot plates based end-effector devices**

For this kind of robot, patient's feet will be positioned on the foot plates, which are controlled by programmable systems to stimulate different phases of gait. An example of footplates based robots is the Gait Trainer GTI (Reha-Stim, Germany) (Fig. 3(a)) [28], which is a servo-controlled gait trainer to help the patient recover his/her lower limb movement ability. It is considered as one of the pioneering robotic systems for rehabilitation [8]. Recently, Hesse et al. designed a lower limb rehabilitation robot called Haptic Walker, which consists of two mechanical plates that can drive the patient's limb to achieve arbitrary movement [21], as presented in Fig. 3(b). Haptic Walker is a major redesign and evolution of GTI. It allows simulation of various gait patterns and adjustable walking speeds. G-EO-Systems (Reha Technology AG, Switzerland) was recently used in a study to simulate the walking and stairs climbing [29]. It consists of two footplates, which can be programmed in vertical and horizontal movements to realize walking and climbing exercise. The G-EO-Systems followed the intention of the Haptic Walker, but specified with smaller dimensions [41]. In these developed robotic devices, however, there are few reports on their ability to stimulate different terrain types. Yoon et al. [42] presented a 6-DOF gait rehabilitation robot, with its foot end-effector designed as a parallel mechanism driven by two linear actuators. It allows patients to update their walking velocity on various terrain types such as walking, stairs and slope climbing. Compared to exoskeleton-based systems, which are able to support the knee during the stance phase, the end-effector based devices, however, may require manual assistance during such a phase.

(a) Gait Trainer GTI [28] (b) Haptic Walker [28]

***Fig. 3.*** Footplates based end-effector devices. (a) and (b)are both reprinted from [28], an Open Access article with unrestricted use permission.




(a) 4-axis redundant parallel robot [33] (b) Rutgers Ankle [20]

***Fig. 4.*** Platform based end-effector robots. (a) is reprinted from [33], with permission from Elsevier. (b) is reprinted from [20], with permission from Springer.

**2) Platform based end-effector robots**

Platform based robots enable the patient to be stationary, just with his/her lower limb (mostly feet) fixed on the platform, which is controlled to perform training programme. Thanks to the features of simple structure and superior adaptability, parallel robots have become more and more popular in platform based medical robots. A parallel robot for ankle rehabilitation was proposed in Istituto Italiano di Tecnologia (IIT) to carry out the required exercises, and a new customized linear actuator was designed [30]. However, the device only allows movements in plantar/dorsiflexion and inversion/eversion. Xie et al. from University of Auckland have developed parallel robots to perform ankle rehabilitation in 3 DOFs [32]. Firstly, a 4-link robot driven by DC motor actuators was designed, then a wearable 4-axis redundant parallel robot driven by artificial pneumatic muscles with flexible and lightweight features (Fig. 4(a)) [33]. However, there are some disadvantages of using artificial pneumatic muscles. For instance, the control methods may become relatively complex when using artificial pneumatic muscles. Moreover, the control bandwidth of artificial pneumatic muscles is relatively low [11] compared to electric actuation one. Rutgers Ankle is a typical ankle rehabilitation robot based on Stewart platform, as presented in Fig. 4(b) [20]. The movement is realized by the coordination control of its six electric cylinders. In [43], the system was further extended to a dual Stewart platform configuration to be used for gait simulation and rehabilitation.

In comparison, exoskeleton robots usually have to be fixed with various parts of human limb to pose different force/torque on different parts at the same time. However, such attachment of exoskeletons would not necessarily good for functional recovery of patients, due to their drawbacks of inferior adaptability to different patients, and the design of exoskeleton robots also is usually expensive and time-consuming [44]. In contrast, end-effector robots usually contact with the patient's body at a certain point, making this kind of robots easy to design and control. Since there is no restriction on the human movement redundancy, the end-effector robots are more easily adaptable to different patients [45]. A recent review [46] study investigating differences between end-effectors and exoskeleton devices found that an end-effector approach may be more favourable for gait training after stroke, although the reason for this superiority are not clear yet [35].

## 3 Robot-Assisted Training Modes

The effectiveness of robot-assisted rehabilitation and therapy largely depends on its ability to assist patients' movement in a number of different modes according to patients' different recovery stages [47]. The appropriate training mode should be determined by physiotherapist's experience and subject's disability levels. As stated in study [30], the rehabilitation process can generally be divided into three stages, namely, the preliminary, intermediate and advanced stages. And during these stages the patient will gradually regain the range of motion and strength at the injured limb or joint. Thus, the patient needs to receive passive and active exercises in different recovery phases. For example, in early stage of rehabilitation, passive mode should be conducted to help patients to track the predefined trajectories to improve the movement ability and reduce muscle atrophy [48]. After a training period once the patient has gained certain degree of strength, active mode should be carried out to encourage patients to trigger the robot assistance by their own active efforts. In this situation, active assist mode means the robot provides assistance when the subject has some voluntary to move but there are inadequate movements, while active resist mode means the subject performs the exercise against a resistive force provided by the robot when muscle strengthening exercises are required [35]. In late rehabilitation stage, the robot is to guarantee patient's balance in the training process and record data for further analysis. Fig. 5 presents two typical control modes for rehabilitation robots: passive mode and active mode [49]. These two mode controllers help the subjects to move their limbs on the desired trajectories or provide assistance to complete the desired tasks. The term for training modes may be stated diversely in different works, but the main idea behind it is similar. A review of robotic training strategies done by Marchal-Crespo [7] employed term “challenge-based” that is similar with the “active resistive” mode here. The “challenge-based" mode refers to the strategy that aims to make patient’s movement tasks more challenging, usually by exerting an additional resistive force to the participant's limb during the training process. Since such a “challenge-based” or “resistance-based” mode would bring enormous benefits to participants with a low level of impairment, many of existing robotic devices have introduced this training mode as one of the most important therapy options to accelerate motor recovery.

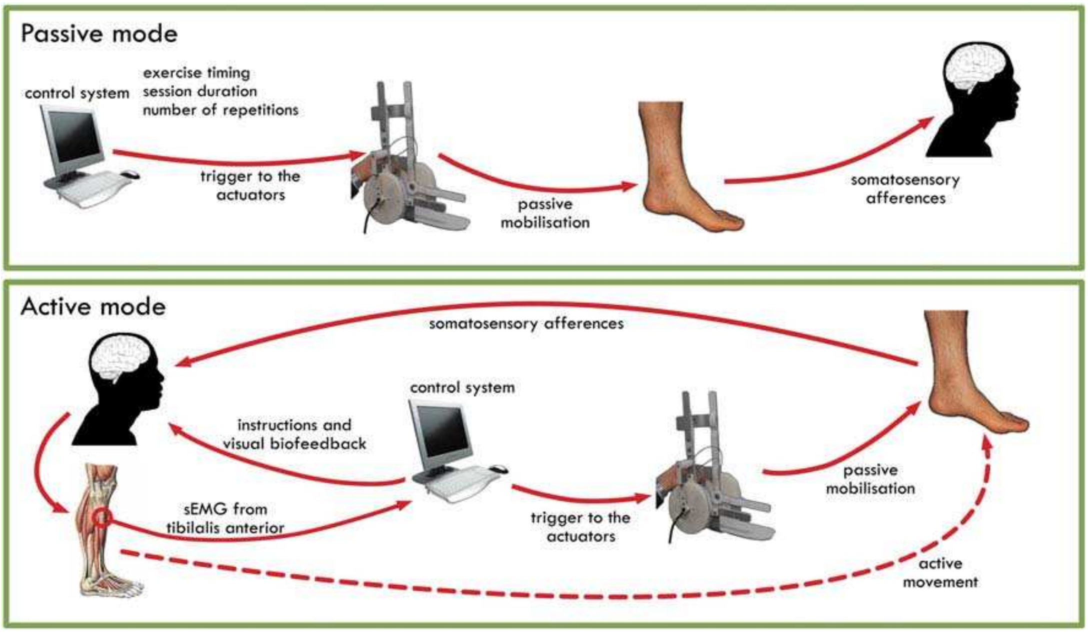



***Fig. 5.*** *Passive mode and active mode*. Reprinted from [49], with permission from Springer.

Recently, more subdivided control modes for lower limb rehabilitation have been proposed. An overview of modes for rehabilitation robot is illustrated in Table 2. Jamwal et al. designed an ankle sprains rehabilitation program that mainly included three training modes for different treatment stages [48]. Considering acute rehabilitation phase after the ankle injuries, an initial stage was added to promote healing of injured tissues before robotic training begins. Then, “passive” mode involving pain-free ROM exercise and “active” muscle strengthening exercise with adjustable resistance level were carried out. To investigate the effectiveness of such control modes on different devices and different limb joints, they have also applied the training modes to a robotic gait orthosis [50]. For severely impaired subjects, position control was performed as “inactive” mode in which the orthosis was controlled to guide patient’s leg on the reference trajectories. In “active” mode, the orthosis provided less assistance to the subject who was capable of having more kinematic freedoms and contributing more voluntary efforts in the gait training process [51]. Saglia et al. from Istituto Italiano di Tecnologia also employed both patient-passive and patient-active exercise modes on their ankle rehabilitation robot ARBOT [31]. In this study, a passive exercise was performed in early stage of therapy when the patient cannot move his or her foot alone. While two different active exercise modes were designed to meet the requirements of particular rehabilitation phases. In moderate stage when patient had certain torque levels, the active “assistive” mode was conducted to provide additional efforts to patient’s movement. In the last stage of rehabilitation, active “resistive” mode was implemented to undergo proprioceptive training and isometric muscle strengthening exercise. Veneman et al. from University of Twente allowed both “patient-in-charge” and “robot-in-charge” modes in a newly developed gait rehabilitation robot LOPES [18]. In fact, these two control modes are almost consistent with the patient-active and patient-passive modes mentioned previously. The robot-in-charge mode is actually a position control mode in which the robot is driven to guide the inactive subject on a gait-like trajectory, while the patient-in-charge mode is dominated by the subject who is able to walk freely within the device and control the robot at will. One distinguished mode in LOPES is the “therapist-in-charge” mode, which is conducted between the patient-in-charge and robot-in-charge mode, means that both patient’s own walking efforts and the robot assistance level will be considered to select the most appropriate torques applied to the leg-joints.

***Table 2** Overview of typical training modes for lower limb rehabilitation robot*

| Control modes | Description | Representative works | Outcomes |
|---|---|---|---|
| Passive mode | Refers to “inactive”, “position-control” “robot-in-charge” mode; robot helps the patient to track the predefined trajectories to perform passive training through repeated tracking control. | Ankle robot and gait orthesis, Xie et al. [48] [50] [51]<br>ARBOT, Saglia et al. [30] [31]<br>LOPES, Veneman et al. [18] | Promote limb motor function recovery and reduce muscle atrophy by repeated intensive exercise, but lack patient’s motivation |
| Active mode | Also refers to as “patient-in-charge” mode; robot modifies its trajectory or assistance force when the subject has some voluntary to move. | Ankle robot and gait orthesis by Xie et al. [48] [50] [51]<br>LOPES, Veneman et al. [18] | Modify trajectory based on patient’s intention, so that the initiative motivation can be greatly enhanced |
| Active assist mode | A kind of “active” mode, similar with “therapist-in-charge” mode; patient moves the limb without assistance first, and when the criterion reaches a threshold, the robot will be triggered. | ARBOT by Saglia et al. [30] [31]<br>LOPES, Veneman et al. [18]<br>Ankle robot, Pittaccio et al. [49] | Allow the patient to move without robot first, so the self- initiative movement ability can be improved |
| Active resist mode | A kind of “active” mode; also refers to “challenge-based”, “active-constrained” mode; robot provides resistance force when patient moves the limb; to make the exercise more challenging. | ARBOT by Saglia et al. [30] [31]<br>Marchal-Crespo et al. [7]<br>Ankle robot, Pittaccio et al. [49] | Suitable for highly recovery patients, resistance make the movement more challenging and can strengthen muscles |
| Other modes | “Bimanual” mode to complete mirror-image movements; or the isotonic, isokinetic, and isokinetic exercise modes that are inspired by manual therapy types. | MIME (for upper limb) [52]<br>Physiotherabot [47]<br>Therapeutic-exercise-supporting manipulator [53] | Developed from the view of therapist, also attempt to provide a certain assistance or resistance level to user |

Besides the common training modes used in robot-assisted rehabilitation as described above, some newly developed modes have also been proposed due to their unusual robotic structures or particular training purposes. For example, motions of the unimpaired arm can be recorded and used to control the impaired limb via a robotic device by adopting the so-called “bilateral” mode. MIME is a typical and well known robotic rehabilitation device that employs this training mode. In fact, four robot assistance modes have been employed by the MIME system [52]: passive mode (the subject relaxed while robot moved the limb to follow a predetermined trajectory), active-assisted mode (patient reached an initial position to trigger the robot assistance), active-constrained mode (the robot provided a viscous resistance in the desired direction and spring-like forces in others), and bimanual mode (robot measured the unimpaired limb's motion and controlled the affected forearm to complete bimanual mirror-image movements). Another tendency in robot-assisted rehabilitation is to design the training modes by considering the conventional therapeutic exercise types. Study [47] presented a series of training modes inspired by the exercise types manually provided by a therapist. The isotonic exercise (moving the resistance through a range of motion), isokinetic exercise (fixed joint angle against fixed resistance), isokinetic exercise (stable movement speed with maximum resistance), as well as manual exercise (active and passive exercises performed by a physiotherapist) modes were realized by using a lower limb rehabilitation robot Physiotherabot. Likewise, study [53] also offered an isokinetic exercise treatment of knee joint that is able to provide variable resistance to a movement with constant speed. Although these new training modes are developed from the perspective of therapists, the connotation in them are similar, as they also attempt to provide a certain level of assistance or resistance to the patient during robotic therapy.

## 4 Control Strategies for Robot-Assisted Rehabilitation

The goal of robot-assisted lower limb rehabilitation is to reinstate neuroplasticity by using various control strategies to improve the motor function of patient's lower limb. Control strategies of robots involving physical interaction with patients' lower limb are thus the most important issue. In recent years, people have tried to extract more useful information from patient's bio-signals which can effectively reflect patient's movement intention and muscle activation. Thus, one of the most popular areas is to integrate the hybrid data fusion (position, force, and bio-signals) and adaptive tuning law into robot control to make it be adaptable to particular patients. With the consideration of training purpose and controller development progress, the control strategies reviewed in this section can generally be divided into four categories: position tracking control, force and impedance control, bio-signals based control and adaptive control. An overview of control strategies for robot-assisted rehabilitation in recent years is summarized in Table 3.

### 4.1 Position-based tracking control

Position based trajectory tracking control is important in early rehabilitation stage when "passive" mode is required, which can help the impaired limb achieve continuous and repetitive training. The primary issue needs to be addressed in position control is how to generate a proper trajectory. Emken et al. proposed a trajectory generation method by using "teach-and-replay" technique with the ambulation-assisting robot ARTHuR [54]. Specifically, the device was firstly passively attached to the limb and the stepping kinematics will be recorded during manual assistance. The recorded kinematics was then replayed to generate a participant-specific stepping trajectory by using proportional-derivative (PD) controller. This method is able to reproduce the gait patterns in high accuracy with the subject's stepping trajectory slightly altered only. Recently, a new method called Complementary Limb Motion Estimation (CLME) for online trajectory generation has been introduced by the designer of LOPES gait rehabilitation robot [55]. In this study, the reference motion for the affected leg was generated based on the movements of the other unimpaired leg by adopting instantaneous mapping between them. However, such trajectory generation algorithm can only be applied for hemiparetic subjects. Apart from the path planning methods to generate a fixed reference trajectory, another strategy that allows both spatial and temporal deviations from the

***Table 3*** *Overview of control strategies for robot-assisted rehabilitation*

| **Control strategies** | **Methods** | **Characteristics** | **Representative studies** | **Outcomes** |
|---|---|---|---|---|
| Position control | Trajectory tracking control | It is the basis for other strategies; repeated passive training can be achieved by this strategy; the trajectory generation and high control accuracy are key issues. | Emken et al. [54], Vallery et al. [55], Duschau-Wicke et al [56], Saglia et al. [31], Jamwal et al. [48], Hussain et al. [50], Beyl et al. [57] | Essential in early rehabilitation, help to achieve continuous and repetitive training but in a passive way, lacking initiatives |
| Force and impedance control | Hybrid position/force control | It can be applied for strengthening exercises; selection matrix can be used to divide the control into an independent position control loop and a force control loop. | Ju et al. [58], Simon et al. [59], Deutsch et al. [60], Bernhardt et al. [61], Banala et al. [62], Duschau-Wicke et al [56] | Robot moves along the desired trajectory and maintains certain interaction force, thus can help strengthen patient's muscles |
| | Impedance control | It is one of the most appropriate approaches for rehabilitation; can regulate the dynamic relationship between robot position and contact force; more and more devices are using impedance control algorithms. | Duschau-Wicke et al. [56], Veneman et al. [18], Hussain et al. [51], Roy et al. [63], Emken et al. [64], Koopman et al. [65], Agrawal et al. [66] | Human-robot interaction will be enhanced, the impedance can be adjusted to make the robot compliant, flexible, adaptable to patient's recovery needs |
| EMG-based control | EMG-triggered control | It is a muscular activation controlled method; predict patient's motion intention in advance and the robot assistance will be triggered when it reaches a certain threshold. | Krebs et al. [67], Kiguchi et al. [68], Kawamoto et al. [69], Fleischer et al. [70], Yin et al. [71] | It encourages self-initiated movement by patients, but there is no interaction during the robot movement until the next EMG trigger occurs |
| | EMG-based continuous control | It utilizes EMG signals to decode the human motion, e.g. estimate the joint angle or torque; control robot in a continuous way, or provide continuous torque assistance proportional to EMG signals. | Song et al. [72] [73], Komada et al. [53], Lenzi et al. [74], Sawicki and Ferris [25, 75], Fan et al. [76] | Patient can keep controlling the robot during exercise, instead of just triggering the robot once, can provide a continuous interaction to the patient |
| Adaptive control | Movement ability-based adaptive control | It can make the robot's behaviour more flexible and adjustable to the patient's ability and participation; set the robot assistance level to patient's movement ability in terms of active force or tracking errors. | Emken et al. [54], Hussain et al. [51], Riener et al. [77], Wolbrecht et al. [78], Blaya and Herr [24] | Patient can take the maximum efforts instead of relying on robot, by adjusting the robot impedance and assistance level when patient shows a better movement ability |
| | EMG-based evaluation and adaptive control | It enables the robot be controlled in a more natural way using muscles; it builds the relationship between EMG signals and muscle activity and adjusts the robot assistance level to patient's muscle recovery needs. | Colombo et al. [79], Krebs et al. [67], Kiguchi et al. [80, 81], Zhang et al. [82], Kwakkel et al. [9] | Robot assistance force and impedance can be adaptable to patient's muscle activity level, enhance the robot's adaptive adaptability and improve the human-machine interaction |
| | Assist-as-needed control | It is one of the most prevailing paradigms to encourage patients' active participation; also refers to as cooperative, adaptive, interactive control; It considers the patient's intention rather than imposing an inflexible control strategy; it can do the exercise like a physiotherapist. | Marchal-Crespo and Reinkensmeyer [7], Riener et al. [77] [83], Duschau-Wicke et al [56], Banala et al. [62], Fleerkotte et al. [39], Hogan and Krebs [84], Wolbrecht et al. [78] | AAN methods can be adaptive to patients' needs and assist the movement only as much as needed, encouraging them to take maximal voluntary efforts |

given trajectory is “path control” strategy. It was proposed by Duschau-Wicke et al. for Lokomat robot assisted gait rehabilitation [56], in order to provide compliant virtual walls around the desired spatial path to keep the patient’s legs within a physiologically meaningful “tunnel”. The initial purpose of this “path control” is to realize a kind of “patient-cooperative” strategy that allows patients to influence their leg movements actively, which is actually an impedance-based control. We will take a more detailed discussion on this in following parts.

Once the desired motion pattern is determined, trajectory tracking control strategy must be developed to guide the patient’s limbs on the reference trajectories. The implementation of trajectory control strategy largely depends on the robot’s mechanical design and structure. The ankle rehabilitation robot ARBOT developed by Saglia et al. is basically a platform-based robot with 3UPS/U1 parallel mechanism [31]. A computed-torque controller with inverse dynamics was implemented to follow the reference trajectory. In comparison, study [6] described a lower limber exoskeleton with 4 DOFs in hip, knee, and ankle. Since the exoskeleton robot can be regarded as a nonlinear dynamical system with uncertainties from human limb and robot, an adaptive and robust learning control scheme was developed to solve time-varying uncertainties in the robotic mode. However, rehabilitation robot is a dynamic and uncertain system. Hence, it may be hard to achieve ideal results by using “model-based” controllers, even though an additional controller can be used to compensate for modelling errors. Jamwal et al. developed a wearable parallel robot for ankle rehabilitation driven by pneumatic muscle actuators (PMAs) [48]. A fuzzy logic controller based on Mamdani inference was designed to work with a disturbance observer to compensate the nonlinear characteristics of PMAs. Though the robot was able to track the desired trajectories, incoherent tracking errors were recorded, especially when interacted with the ankle. Moreover, fuzzy controller has its inherent limitations, e.g., the fuzzy rules are always hard to formulate and the inference process may take a long time. Xie’s group further presented a chattering-free robust variable structure based trajectory tracking controller for a robotic gait orthosis powered by PMAs [50]. Such control scheme can achieve a quite satisfied tracking performance, however, this study did not consider the gait trajectory with changeable speed that is very important in different human walking phases. As changeable gait speed may bring unstable and unsafe factors to the robot control, large deviation errors will probably happen in this situation. Considering safety prerequisites for training, study [57] proposed a proxy-based sliding mode controller (PSMC) for a gait exoskeleton with its knee joint also powered by pneumatic artificial muscles. This PSMC can potentially be a safe “robot-in-charge” control strategy since it combines both a good tracking accuracy to the normal reference trajectory and also a safe response to large position errors. However, the position based tracking controller only guides the patient’s limb strictly follow on a predefined trajectory rather than a trajectory customized specifically to the patient, without taking into account the patient’s active interaction, thus it may reduce the participant’s voluntary participation and motivation.

### 4.2 Force and impedance control

#### 1) Hybrid position/force control

Patients are usually trained in a passive way and lack initiatives and motivations in purely position-based tracking control. Fixed repetitive training might cause inactive response from the patient and result in negative training effects. Hence, hybrid position/force control considering the interaction between human subject and the device plays an important role in training. This method can be applied for strengthening exercises. Ju et al. designed a hybrid position and force controller which can guide the patient move along a linear or circular trajectory and maintain a constant contact force [58]. Since the system may become unstable in this direct force and position addition control scheme, Simon et al. from University of Michigan introduced a novel method of controlling the interaction force during lower limb extensions [59]. The purpose of this study is to provide the target resistance force to the impaired limb for improving force symmetry in the limbs. Similarly, the developers of Rutgers Ankle also proposed a high-level position and force controller to supply 6-DOF resistive forces on the patient's foot, in response to virtual reality-based exercises [60]. The established haptic interface was used to read the foot position and orientation and then exerted resistive forces for lower-extremity training with an interactive virtual environment (VE) simulation. A distinct advantage of such hybrid position/force strategy is that the robot can be controlled to move along the desired trajectory and maintain a certain human-robot contact force, which can help strengthen patient's muscles and enhance recovery.

However, such control strategies only allow the participant to exert certain resistance force along a fixed trajectory and do not allow voluntary active movements of the patient. Riener's group presented a new hybrid force/position control architecture to enhance active contribution of the patient in the gait robot Lokomat [61]. This control structure consisted of a closed-loop PD position controller and a force controller, and these two loops would be switched between swing and stance phases. The required robot assistance force, calculated by using a dynamic model, was controlled to guide participant's leg and would be reduced by a certain percentage to enable patient's voluntary walk. The great advantage of this strategy is that the patient has maximum freedom to change the gait trajectories. However, it must be noted that the arbitrary modification of gait pattern may result in an un-physiological path that may cause secondary injuries to the patient's limb. To address this problem, adopting a new force/position control method that is able to move the patient along the physiological trajectory and also exert normal forces seems an optimal choice. ALEX is an active leg exoskeleton for gait rehabilitation controlled in such an approach implemented by Banala et al. [62]. A force-field controller was applied in this study to apply suitable interaction force between the subject and the orthosis to help the leg move on a desired trajectory. The goal of this controller is to assist or resist the motion of the leg by providing less resistance when the subject moves on the desired gait trajectory and higher impedance if deviates from it. This kind of method also can be called "virtual tunnel" approach, since in this scheme the tangential force is controlled to move patient's limb along the trajectory and the normal force is used to keep the limb move within a virtual wall [65]. A similar virtual tunnel strategy is implemented in the Lokomat by Duschau-Wicke et al [56]. In this study, a path control strategy with "virtual walls" was proposed to constrain the patient leg's movement within a region of "tunnel" around the desired spatial path in joint space. In fact, this is a kind of "patient-cooperative" strategy that allows patients to influence the gait pattern, but ensures to limit the path within the range of being physiologically meaningful [10]. This kind of cooperative control strategies will be focused in section 4.4.

**2) Impedance control**

To encourage active participation and allow patient's natural variability, real-time adjustment of desired dynamic relationship between robot position and contact force is essential. Impedance control strategy is one of the most appropriate approaches to achieve this purpose [85]. Nowadays, more and more robotic devices control the interaction forces by using impedance control algorithms. MIT-Manus utilized impedance model to adjust the robot compliance [66], and Lokomat also used impedance controller to regulate the patient's gait speed and traction force for each leg [56]. In [18], "robot-in-charge" and "patient-in-charge" control strategies were implemented for LOPES by using impedance controller to enhance patient's active participation. However, impedance control also introduces new challenges: the impedance parameters should not be always fixed. As different impedance parameters will make the robot reveal different compliance, low impedance levels increase the risk that the patient move beyond the physiological range of motion. In contrast, high impedance parameters will probably force the patient in a passive state and hardly achieve active training [55, 86]. As the patient's movement ability is changing over time, the impedance parameters have to be re-selected to match patients' capabilities and progress [65]. So, adaptive methods are urgently necessary in rehabilitation robots to guarantee the dynamic performance. Xie's group [50] have proposed an adaptive impedance controller with maximum and minimum compliance modes. In "minimum compliance" mode, the participant is completely passive and the robotic orthosis is run under 100% force to drive the limb on a reference trajectory; while in "maximum compliance" mode, the human has more freedom and can drive the robot to deviate from the reference trajectory. This compliance mode is similar with "robot-in-charge" and "patient-in-charge" mode proposed by Veneman et al. [18]. But, a common limitation existing in both is the discontinuous model, just like to turn on or off the robot assistance, rather than offering a seamless impedance tuning process.

To tackle this problem, the patient's disability level or human-robot interaction has to be estimated and used to adapt the robotic compliance. As a result, Xie's group further proposed an adaptive impedance controller for the robotic orthosis to provide interactive gait training [51]. The objective of this adaptation law is to adjust robot impedance based on subjects' active joint torque estimated from human-robot interaction force. However, for particular patients such as stroke survivors with foot drop problems, this torque estimation is not available for impedance tuning any more. To facilitate an accurate estimation of ankle stiffness, Massachusetts Institute of Technology (MIT) developed a novel robot for ankle assessment and rehabilitation [63]. A simple approach by using this robot is to statically measure the angular displacements and the total torques and then obtain the passive stiffness by calculating the ratio of torque to angular displacement. It potentially provides a clinical measurement tool to estimate ankle stiffness that can be used to adjust the impedance level of robotic device for variable recovery phases. Moreover, Koopman et al. designed an impedance controlled exoskeleton (LOPES) for gait assistance [65], in which a Virtual Model Controller (VMC) was used to select proper subtasks according to the capabilities and progress of the patient. In addition, an adaptive algorithm was employed to shape the amount of support within each subtask automatically by modifying the virtual stiffness at each percentage of the gait cycle. However, impedance method is usually realized based on force-triggered assistance, which means the patient must have sufficient voluntary force first, and then the robot assistance can be triggered. In this way, the control process may inevitably be divided into two separated parts: a patient-driven part and a robot-driven part, instead of providing a seamless robot assistance [78]. Although the continuous robot assistance can be realized by adopting online trajectory adaptation method, which means keep sensing patient's interaction force and modifying the trajectory in a continuous way. However, the issue of trajectory adaptation based on adaptive impedance model is still unresolved, as the modified trajectory may result in an un-physiological limb movement pattern.

### 4.3 Bio-signals based control

Bio-signals contain more useful information about human limb movements. It enables the robot to be controlled in a more natural way by using EMG signals recorded from participant's muscles. It has been found that a considerable correlation exists between EMG signals, limb movement, and muscle activities [87]. Therefore, with the recent development of bio-signals processing techniques, the robot control based on bio-signals has become a popular research area [88, 89], in which EMG-triggered and continuous control are two typical EMG based strategies.

**1) EMG-triggered control**

EMG signals are generated before limb muscle contraction, so it can be used to predict the movement intention in advance [74]. For example, Krebs et al. [67] proposed a performance-based progressive robot control mode, which allowed the patient to move the limb without assistance first, and when the EMG value reached a certain threshold, the robot assistance would be triggered. In order to realize EMG-triggered control, patient's movement intention must be identified accurately by using EMG features extraction and pattern recognition methods [90]. Among these classification algorithms, neural networks are widely used in recent studies to improve the recognition accuracy [68, 91-93]. Kiguchi et al. designed a neuro-fuzzy controller to identify the movement pattern of the forearm by using EMG signals [68], and a probabilistic neural network was proposed in [91] for EMG patterns discrimination. In [92, 93], wavelet packet features were used to extract useful information from EMG, and the gesture mapping relationship was established by using BP neural network, too. However, these methods are complicated and require huge amount of signal samples, making the real-time performance of the EMG controller unsatisfied. On the other hand, since the strict requirement of the real-time control for the lower extremity is different from that of the upper limb, there have been relatively few studies that have used powered robotic devices for the lower limbs to study the neural control [94]. For the lower exoskeleton system HAL, EMG signals were used to measure the human-robot interaction and estimate the intention by discovering the relationship between joint torque and corresponding EMG signals [69]. In order to make the feature extraction more precise and the recognition result more reliable, new methods need to be introduced to decode participant's lower limb motion. Study [95] describes an intent recognition approach for a powered lower limb prosthesis by using prosthesis sensor data. The time-based features of prosthesis mechanical signals were extracted and used to train intent models such as standing, sitting, or walking. Fleischer et al. presented a method to calculate the human gait pattern intention during walking for an exoskeleton by combining EMG signals and pose sensors [70]. The EMG signals were used to calculate the muscle forces and the position data to obtain the gait posture. The calculated muscle forces were then used to estimate the knee torque and eventually the angular acceleration [11]. Although EMG-triggered control encourages self-initiated movement by patients, but, when the robot is driven to provide assistance after being triggered, typically passive training will be performed in EMG-triggered control to achieve the necessary movement, so the patient is not in a fully compliant environment when assistance is provided.

**2) EMG-based continuous control**

In EMG-triggered control mode, the robot would operate with a predefined trajectory after being activated, which had no interaction with the human limbs during this period until the time allowed for the next trigger event. This kind of "on-off" control might limit the interaction between the external assistance and the EMG signals that indicate participant's active intention. In order to resolve this problem, EMG-based continuous control methods are developed recently to improve the patient-active performance. Song et al. developed a myoelectric control robotic system to provide continuous stretching assistance torque whenever the EMG signals exist [72]. The provided assistance driven by myoelectric signals was controlled to be proportional to the amplitude of EMG signals [73]. An advantage of this continuous proportional myoelectric control is it provided more opportunities for subjects to interact with the device interaction during the whole motion. However, the relationship between EMG and joint torque in the present study was simplified as a linear model, and the muscle activity condition of the patient was not taken into account. Komada et al. described a manipulator with a biofeedback function [53] that can estimate a person's joint torque and muscle activity by applying a musculoskeletal model. The modelling accuracy was then evaluated during walking exercise by comparing it with the EMG waveforms. However, its usability is strongly limited, since the musculoskeletal model widely varies between different users and sessions, which confine their use to the laboratory environment. Lenzi et al. studied a new method to provide assistance through a proportional EMG control applied a powered exoskeleton [74]. This system only roughly estimated the user muscular torque without calibration, with results showing that subject's EMG signals can almost instantaneously adapt the robot assistance. However, similar with Song's system, only one degree of freedom robot-aided movement was tested in current study. Sawicki and Ferris also applied an EMG proportional controller to a knee ankle-foot orthosis (KAFO) with 3 DOFs [25]. Different from Lenzi's robot, it is the pneumatic muscles of the orthosis that were controlled by using surface EMG signals from the user's muscles. In this control scheme, the air pressure of each artificial pneumatic muscle was directly proportional to the EMG signal when the its amplitude was between the minimum threshold and the maximum saturation [75]. Experiments have verified the advantage of proportional myoelectric control in providing a direct link between the user's nervous system and the exoskeleton torque. However, proportional EMG control has specific disadvantages: It might be difficult to obtain a reliable control command by using EMG signals only, due to the surface electrode interface and the synergistic co-activation effects between different muscles. Hence, mechanical sensors which can provide kinematic or dynamic data of the human-robot system should also be equipped as compensation signals to the EMG. Study [71] presented an active control method by using multi-source data fusion in a lower extremity exoskeleton system, bio-signals and force information were integrated to decode the human motion and estimate the joint angle. This work also indicates that hybrid data show a better performance than using EMG only.

### 4.4 Adaptive control strategies

Traditional robotic rehabilitation devices cannot perform training similar to manual assistance provided by a therapist, who is able to match the individual needs and assist the patient's movement only as much as needed. Study [7, 9] suggest that the most effective control strategies for robotic rehabilitation may include three categories, namely, impedance-based active control, EMG-based active control and adaptive control based on patient's conditions. And adaptive impedance control is more likely to achieve better rehabilitation effects for its ability to make the robot's behaviour more flexible and adjustable to the patient's capabilities, progress, and participation.

#### 1) Movement ability-based adaptive control

Patient's movement ability can be estimated from contact force/torque [31, 51], quantitative efforts [39], or trajectory tracking errors [78]. By using adaptive controller, the robot assistance force can be adjusted according to patient's physical movement ability [39]. The adaptive impedance controller applied in [51] adjusted the robot assistance according to human contact force, in which the robot assistance was reduced when patient's active force increased, and vice versa. This study is supposed to be inspired by the “patient-cooperative” strategy proposed by Riener et al. [77]. This is in fact an adaptive impedance controller that utilizes the patient’s contact force information to adapt the robotic assistance and impedance level. The goal of this case is to enable the patient to contribute as much as possible to the movement by changing the desired gait trajectory. However, as explained above, a question with this approach is that the arbitrary deviation from the reference trajectory may lead to an un-meaningful gait pattern. Emken et al. demonstrated an adaptive learning control law that can adjust robot impedance according on a step-by-step basis [54], which means the robot assistance was provided only when the subject exhibited trajectory errors. By introducing such a forgetting process, more variability is allowed in each gait step to enable more patient’s active participate during the robotic exercise. Therefore, a distinct advantage in Emken’s work is that it allowed movement freedom within small errors while keeping the gait path along a reasonable range of the desired trajectory. Meanwhile, such adaptive controllers with forgetting factors are able to reduce the robot assistive force to a minimum, so as to avoid patient’s overly relying on robot assistance. Wolbrecht et al. also introduced the forgetting factor to robot controller [78], so the robot assistance can be reduced and stiffness and damping parameters can be adjusted when patient’s self-initiated trajectory tracking error is small enough. Blaya and Herr proposed an impedance-based adaptive control strategy to control their ankle-foot orthoses [24], with its stiffness being adjustable to movement performance evaluated from previous sessions. The primary purpose of such movement ability-based control is to maximize patient’s voluntary efforts. The impedance can be automatically adjusted to make the robot maintain a high compliance and also provide sufficient assistance to complete the assigned movement task.

**2) EMG-based evaluation and adaptive control**

Patient’s muscle activity and recovery conditions can be reflected by EMG signals, and the robot assistance should be adaptable to patient’s muscle activity during robot-assisted therapy. Specifically, in early rehabilitation stage, the muscle activity is in low level and muscle strength is weak, then the robot damping should be small, so that patients can control the robot more easily; while in the late stage, the impedance should increase when muscle activity level is high, so as to generate greater interaction force and make the exercise more challenging. Colombo et al. described a robot device that could adapt training to the individual by selecting motor tasks of different difficulty levels to match each patient's ability [79]. This will bring more benefits to patient's training and recovery [52]. To sense patients’ muscle ability, many recent studies [81, 82] have focused on the estimation and evaluation of muscle activity levels based on EMG signals. Isometric muscle model is traditionally used to establish the nonlinear relationship between EMG and muscle forces [96]. However, human body segments and muscles are unique to individual subjects, thus the universality of this model cannot be guaranteed. Recently, neural networks have been adopted in robot-assisted rehabilitation to map EMG signals to muscle forces. Choi et al. predicted the pinch force from EMG segments by using artificial neural network [97], and a nonlinear force prediction model was established via BP neural network [82]. Also, neuro-fuzzy matrix was adopted in [81] to build the relationship between EMG and joint torque. However, the level of EMG readings is dependent on the skin impedance at the electrodes location, which may vary between different training sessions. EMG signals have to be combined with other sensor data to improve the evaluation effectiveness. Study [76] presented an example of adaptive control strategy by integrating EMG signals and hybrid multi-source data fusion, where EMG and force-position data are integrated to realize progressive exoskeleton-assisted training. One critical issue in hybrid control is to introduce the assessment methods to evaluate the patient’s muscle strength, activity level, fatigue, etc., so that the robot can perceive the patient’s limb status and take appropriate control strategies. In [80], a hybrid control method was proposed by estimating the patient’s joint torque from EMG signals and then to control the robot. Compared to other methods, an important advantage of the EMG control is that the robot can be controlled in a more natural way using his/her own muscles. Unfortunately, it is found that only a few studies have introduced EMG signals into the whole robot control lifecycle.

**3) Assist-as-needed control**

To further increase patient’s motivation, there is a growing tendency towards assist-as-needed control strategies, in which the system adaptively takes into account patient's ability and provides assistance only when needed, rather than imposing an inflexible control strategy. Controllers based on this principle are also referred to as “patient-cooperative”, “human-centred” or “progressive” controllers [65]. A comprehensive review on this kind of control strategies for robotic training has been conducted by Marchal-Crespo and Reinkensmeyer [7]. The “patient-cooperative” technique was first proposed by Riener et al. [77] for Lokomat robot-aided gait rehabilitation. This strategy can adapt the robotic assistance or adjust the reference trajectory to individual subject’s contribution. The first experiment of “patient-cooperative” strategy utilized force sensors to detect the patient’s muscular efforts to regulate the robotic assistance. This “patient-cooperative” approach is important for patients’ rehabilitation for its capacity to stimulate patient’s active participation and increase the motivation. Riener et al. also proposed a kind of “subject-centred” strategy [83] that can be regarded as another expression of “patient-cooperative” approach, since both of them focused on recording the patient’s movement efforts and using them to adapt the robot impedance and assistance outputs. The “patient-cooperative” technique was further evolved into “assist-as-needed” by introducing a “path control” method, in which a compliant virtual wall was developed to keep the patient’s legs within a “tunnel” around the desired gait trajectory [56]. Similar AAN approaches were applied by other robots such as ALEX [62]and LOPES [39]. In these systems, the desired motion was determined by a healthy spatial path with a “virtual wall” or force field controller that can make the robot be flexible and adaptive to user’s needs. Such AAN strategies are able to reduce the chance of the user becoming reliant on the support, since the stiffness and width of the “tunnel” can be adapted to participant’s performance to make the robot provide assistance only as much as needed. The concept of “assist-as-needed” is also a key part of "performance-based, progressive” control strategy developed by Krebs et al. for MIT-Manus [67]. This study presented a novel algorithm that is capable of continuously engaging the patient in the activity to maximize the chances to achieve optimal motor recovery. This “progressive” therapy was developed by using an adaptive impedance controller, whose parameters can be varied according to patients’ performance evaluated from last several sessions [84]. Specifically, if the patient showed a higher performance with fewer movement errors, the stiffness and the robot assistance were thereby reduced, and vice versa. In study [78], the assist-as-needed scheme was achieved by using a force reducing term in order to adapt the robot assistance force if the patient’s tracking errors were small. This “optimizing compliant” controller allowed the robot to remain its supportive assistance to a minimum compliant while assisting the patient to complete movement tasks. Nowadays, the assist-as-needed control concept has become one of the most prevailing paradigms in order to encourage patients’ active participation during robot-assisted rehabilitation. In this way, a physiotherapist-resembled therapy can be enabled by continuously changing the interaction between robot and patient.

## 5 Discussion and Conclusion

Robot-assisted lower limb rehabilitation has a variety of advantages over traditional manual therapy and training, and shows encouraging clinical outcomes and recovery efficiency. Existing studies have also demonstrated the effectiveness of robot-assisted lower limb training. In this review, various studies are conducted to compare different robotic mechanisms, training modes and control strategies. As the rehabilitation robot directly contacts with the human limb, its workspace and movement features must be considered when designing a mechanical structure. A superior feature of exoskeletons for rehabilitation is the possibility to control the segments of the lower limb since it can be worn by the participant. While the end-effector robots usually contact with the patient's body at a certain point, making this kind of robots more easily adaptable to different patients. In order to improve clinical outcomes, rehabilitation robots should have various operation modes and be adaptable to patients' recovery conditions. The patient-active mode taking into account participant's active intention and voluntary efforts is supposed to be more effective than traditional passive and repetitive training. Contrary to active assist mode, challenge-based robotic training aims at rendering the task more challenging and demanding higher efforts so as to improve motor function. As for the control strategies, impedance control becomes more and more popular in the control of lower limb exoskeletons and platforms, and EMG signals have also been widely used to estimate the human intention prior to the system control. Evidences from many studies show that human-robot interaction is very important in encouraging patient's recovery. An adaptive controller that can sense patient's status and tune the robot compliance to match particular patients is believed to be the most efficient to realize "patient-cooperative" robotic therapy. In the meantime, the assist-as-needed control concept has emerged to encourage the maximum participation of the patient by providing only as much assistance as necessary.

Although most exiting rehabilitation robots are able to provide systematic and prolonged treatment and training sessions, there are drawbacks associated with their designs. In terms of actuators and mechanical designs, artificial pneumatic muscle represents a good choice for wearable robots because of its relatively low weight, high efficiency, and intrinsic safety. However, low control bandwidth and complex algorithms are main challenges that hinder its applications. Trajectory tracking control is the basis and is applied in almost all available rehabilitation robotic trainers. However, this control strategy guides the patient's lower limb on a predefined trajectory without taking into account patient's movement intention, thus reducing user's active participation and motivation. Impedance control based on force feedback allows the patient to deviate from the reference trajectory according to the dynamic relationship between position and interaction force, and thus is more suitable for patients. However, as the impaired limb should be treated with different impedance values and robot compliance, how to determine the impedance parameters is still an open problem. In this situation, robotic training with adaptive impedance model and assist-as-needed control concept is supposed to be the most appropriate method, as the amount of robot assistance can be adjusted to suit patient's recovery conditions and training progresses.

As stated previously, the implementation of adaptive control algorithm ought to its ability to generate different training modes adaptable to patients with different recovery conditions. Thus, one important factor is to evaluate and quantify the patient's movement ability, muscle activity or training progress. To the authors' best knowledge, the patient's muscle activity and recovery status cannot be monitored online in most existing lower limb rehabilitation robots [98]. Most current approaches used kinematic parameters, such as the interaction force, joint angle/trajectory tracking errors, to determine the patient's movement ability, but these data are hard to accurately reflect patient's actual ability [83, 99]. It is expected in the future that the bio-signals (e.g. EMG) must be introduced in the whole lifecycle of robot control, so that the patient's movement intention can be perceived and the muscle activity level can be reflected. However, the major difficulty of the EMG-based evaluation and control could come from the following aspects. Firstly, the EMG signals quality affects the muscle activity modelling. This model will possibly include skin noises of subject's body segments, which are unique to individual subjects, and the EMG magnitudes could change as the training progresses. Secondly, it is not easy to build a universal muscular force prediction model that is suitable for all patients, and it is also hard to evaluate a specific lower limb joint muscle during robot-assisted movement. Moreover, the muscle activity and required robot assistance is changing all the time, so real-time computation is needed to ensure the controller's dynamic performance, which makes the EMG based evaluation even more challenging.

In addition, there are only limited studies of the interactions between robots, patients and physiotherapists. The advanced human-robot interfaces for patients and physiotherapists have not been fully considered in current rehabilitation devices. One study is conducted by Akdogan et al. who developed a lower limb robot to perform exercises and learn specific exercise motions from the physiotherapist through a human–machine interface [100]. Experiments showed that the robot could perform necessary exercise in accordance with the manual trial by physiotherapist. However, whether the mechanical interfaces can improve the patient's clinical outcomes and comfort the body structures with low compliance according to therapist's experience is still unclear. Study [71] has developed a bidirectional human-machine interface by using EMG signals and an extended physiological proprioception (EPP) feedback system. However, the sensitivity of the EMG electrodes, the accuracy of the model between the motion intention and the EMG signals are still challenging problems. Although EMG recordings make it possible to predict human motion intention precisely in advance, some errors may exist due to the rapidly changed direction of the muscle extension of human limb during exercise. Hence, angle and force information which can provide mechanical data of the robotic system must be considered as the compensation signals. On the other hand, many rehabilitation robots lack effective patient evaluation system. As the objectivity of traditional clinical scoring scales is not guaranteed, the question of most effective rehabilitation assessment strategy is still open. Although the introduction of bio-signals makes the objective evaluation possible, how to provide reliable assessment metrics is an unsolved problem.

Future research in the area of robot-assisted lower limb rehabilitation can be summarized as follows. Firstly, the robot-assisted rehabilitation needs to comply with neurophysiological therapy principles. The ability to deliver a variety of control modes that match patient's different recovery stages is one of the prerequisites for robot-assisted rehabilitation. Secondly, in order to get a clear perspective of patient's movement ability and recovery conditions, new assessment strategies should be developed to verify the effectiveness of robot-assisted rehabilitation [101]. Patient's movement ability can be evaluated by robot recording data, while the muscle activity status should be determined from bio-signals by statistically analysing. Thirdly, patient's active participation plays an essential effect on the rehabilitation outcomes. It is critical to adjust the robot assistance force and encourage patient's maximum voluntary efforts during robot-assisted therapy. Further study on the combination of robot control with bio-signals (e.g. EMG) is required to assess patient's muscle activity levels and recovery conditions, and to modify the robot impedance to provide adjustable assistance force for particular patients. To this end, research on novel adaptive control techniques to implement efficient assist-as-needed strategies is also essential in the future. Last but not least, the evidences in effectiveness provided by robot-assisted rehabilitation are less than expected. It is still early to draw a conclusion that all robot-assisted rehabilitation is superior to the conventional manual therapy, though the robot's advantages are obvious. In the future, trials with more patient groups should be conducted to highlight the clinical effectiveness of rehabilitation robots.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## Conflict of Interest

The authors declare no conflict of interest.

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