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Review

Hierarchical Classification of Subject-Cooperative Control Strategies for Lower Limb Exoskeletons in Gait Rehabilitation: A Systematic Review

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Abstract: Over the last decade, lower limb exoskeletons have seen significant development, with a particular focus on improving the interaction between the subject and the exoskeleton. This has been achieved by implementing advanced control strategies that enable the safe and efficient use of the exoskeleton. In this work, the control strategies for lower limb exoskeletons are divided into upper-level control (supervisory and high-level control) and lower-level control (the servo layer). Before discussing these control strategies, a brief introduction to lower limb exoskeletons and their control schemes is provided. The control hierarchy for lower limb exoskeletons is then systematically reviewed along with an overview of the techniques used. A Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) statement is used to highlight the systematic process of identifying relevant articles with inclusion and exclusion criteria. The details of supervisory control, high-level control, and servo control strategies are presented by citing relevant state-of-the-art studies, particularly from the past five years. The targeted lower limb joint, training mode, and development stage for different control strategies are highlighted in a tabulated form to articulate the overall hierarchy level. Finally, the potential opportunities and limitations of subject-cooperative control are discussed. Overall, this work aims to provide an in-depth understanding of the control strategies used in lower limb exoskeletons, focusing on subject cooperation. This knowledge can be used to improve the safety and efficacy of lower limb exoskeletons, ultimately benefiting individuals with mobility impairments.

Keywords: lower limb exoskeletons; subject-cooperative control; supervisory control; high-level control; servo control; hierarchy

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1. Introduction

Locomotion in human beings is a consequence of synchronized movements of arms (upper limbs) and legs (lower limbs) controlled by neuronal networks running through the spinal cord [1]. Optimized into specific rhythms of motion across limbs, this motion is coordinated using the somatosensory feedback and supraspinal pathways, which are prone to being affected by neurological disease or trauma such as spinal cord injury (SCI), stroke, or cerebral palsy (CP). The partial or complete failure of neuronal networks, muscular actuators, and the underlying skeletal members diminishes the ability of a person to move. Functional independence of the person is thereby impacted severely, affecting their sense of autonomy, productivity at work, and their general quality of life. Roughly one billion individuals globally, constituting around 16% of the total population, are currently grappling with disabilities that result in challenges with their lower extremities. These disabilities can present as muscle weakness, partial or complete paralysis, and the absence of support or aid when it comes to lower limb movements [2]. For more than three decades, conventional means have been extensively exploited for motion assistance and augmenting mobility, such as wheelchairs, supporting canes, and stands. However, the traditional approaches have limitations, such as limited mobility, additional in-person assistance, and more dependence on physical therapists for limb rehabilitation. However, as the number of patients increases the manual process becomes cumbersome, as it involves skilled labor, delivers less sustainability, and causes fatigue on the part of therapists. Moreover, the significant benefits of the manual therapy are lost if ever the process is withdrawn for even a short period [3]. Therefore, to address the limitations of conventional methods, the proliferation of exoskeleton technology has been observed for lower-limb rehabilitation [4–8].

1.1. Lower Limb Exoskeletons

Exoskeletons are devices that assist their users in performing several kinds of functions. Lower limb exoskeletons are those that focus on interfacing with the legs of the user and assisting in their locomotion. These can be separated into three categories: assistive, rehabilitative, and augmentative [9].

Assistive exoskeletons are devices designed to support and enhance the physical capabilities of people with limited mobility or strength. These devices work in harmony with the user's existing functional abilities rather than replacing them [10–12]. The exoskeleton typically operates on predetermined motion paths that are tailored to the specific limb or body part that requires assistance. The user only needs to provide input regarding their intention, which can be measured in a variety of ways, and the exoskeleton takes care of the rest. One crucial factor in effectively using assistive exoskeletons is the precision of control. Any deviation from the intended motion trajectory could significantly affect the user. Therefore, it is crucial to ensure that the exoskeleton is calibrated accurately to provide precise and consistent support. Overall, assistive exoskeletons can significantly improve the quality of life for individuals with limited mobility or strength, enabling them to perform tasks they would otherwise be unable to do independently.

Therapeutic or rehabilitative exoskeletons are a type of technology that aims to help patients regain physical abilities and function independently. These devices support the user while gradually reducing the level of assistance required to complete tasks. Ultimately, the goal is to train or retrain the patient's musculoskeletal and neurophysiological systems to function without the aid of the exoskeleton [13–15]. To achieve this, therapeutic or rehabilitative exoskeletons typically use a combination of live feedback from the user and partial predefinition of motion trajectories. As the user becomes more proficient at completing the target tasks, the level of assistance the exoskeleton provides is gradually reduced; more resistance may even be added to provide a further challenge. Because therapeutic or rehabilitative exoskeletons are primarily used in healthcare centers and for specific purposes, they do not necessarily need to be portable. However, they require live adjustments based on user feedback to ensure that they provide the appropriate level of support and resistance for the patient's needs. Overall, therapeutic or rehabilitative exoskeletons can be critical in helping patients to recover physical abilities and regain independence. These devices can provide a valuable tool for physical therapists and healthcare professionals to support patients in their rehabilitation training.

Augmentation exoskeletons are a type of technology that is designed to enhance the functional capabilities of individuals, even those who are otherwise healthy. These devices use advanced tracking technology, such as admittance/impedance control, to monitor the trajectory of the user's limbs and increase the power output of the range of functions they are designed to augment [16–18]. To achieve this, augmentation exoskeletons typically utilize high power-to-weight ratio actuators such as pneumatic actuators and series elastic actuators (SEAs). Moreover, with technological developments in pneumatic artificial muscles [19], muscle fatigue can be reduced by allowing the exoskeletons to significantly boost power without adding excessive weight or bulk to the device [20]. The ultimate goal of augmentation exoskeletons is to enhance the abilities of the user beyond their natural capabilities, enabling them to perform tasks that would otherwise be impossible or very challenging. For example, an augmentation exoskeleton can be used to help individuals lift heavy objects, walk or run faster, or perform physically demanding tasks for extended periods. It is worth noting that this review focuses specifically on the control of assistive and rehabilitative exoskeletons, rather than augmentation exoskeletons.

1.2. Control of LLEs

The effectiveness of exoskeletons is heavily dependent on the control strategies used to operate them. These strategies determine which inputs from the user are considered and how they are transmitted to the actuators that control the movement of the exoskeleton. The overall control strategy needs to take into account the actuator drivers and the movements of the limbs both with and without the user wearing the exoskeleton. Assistive and rehabilitative exoskeletons often rely on subject-cooperative control strategies, which involve the user's active participation in the movement of the exoskeleton. These strategies are designed to enhance motor recovery at various stages of treatment and rehabilitation. The neurophysiological aspects of locomotion, including the plasticity of the human brain, are taken into consideration when designing these strategies in order to reinforce beneficial activities [21,22].

Subject-cooperative control approaches are used in various rehabilitation modalities, including *passive*, *active*, *active-assistive*, and *resistive* strategies. The success of these strategies is heavily reliant on user feedback from the human–robot interaction model. By considering the input and feedback from the user, exoskeletons can provide more natural and effective assistance in movement, improving the recovery process [23,24]. In the case of *passive* mode, the patient's capacity to move is considered to be nil and feedback need not be considered for the initial stages of rehabilitation until activity growth is detected. Provided that the subject lacks significant muscle strength, the robot acts by itself based on servo control schemes. In *active* mode, exoskeleton control neither aids nor inhibits function, and behaves in compliance with the defined gait trajectory. However, resistance is provided in case of deviations from the set profile in order to course-correct the user onto the predetermined gait path. In cases where the human user has partial ability to perform functions, *active-assistive* modality provides for the remaining required effort to be provided as assistance. *Resistive* mode provides a degree of resistance to the user in order to force the user into repetitively applying greater than necessary effort, thereby strengthening the neurophysical and musculoskeletal elements of that particular joint. In cases involving lower limb rehabilitation, passive and active training modes are the most used in the literature, as shown in Table 1.

Table 1. Recent studies on gait exoskeleton control strategies.

Study (Year)	Targeted Joint	Training Mode	Upper Level (Decision Layer)		Lower Level (Servo Layer)	Development Stage
			Supervisory Level	High Level		
Ayas and Altas [25] (2017)	A	P, A	-	Adaptive Admittance (Fuzzy logic based gain regulator)	Fuzzy logic control	E
Chen et al. [26] (2017)	HKA	P	FSR, IMU	-	PD	C ($n_h = 1, n_p = 1$)
d'Elia et al. [27] (2017)	H	P	Optoelectronic	-	Adaptive oscillators	C ($n_p = 5$)
Patane et al. [28] (2017)	KA	P	IMU	-	PID	C ($n_p = 3$)
Yang et al. [29] (2017)	H	P, A	-	-	Command filter backstepping SMC	S
Lerner et al. [30] (2018)	A	P	FSM, FSR	-	PID	C ($n_p = 5$)
Khamar and Edrisi [31] (2018)	K	P	-	-	Backstepping SMC + nonlinear disturbance observer	S, E
Luo et al. [32] (2018)	HK	A	-	Adaptive impedance (Fuzzy logic based gain regulator)	-	S
Han et al. [33] (2018)	HKA	P	-	-	Adaptive non-singular fast terminal SMC	S

Table 1. *Cont.*

Study (Year)	Targeted Joint	Training Mode	Upper Level (Decision Layer)		Lower Level (Servo Layer)	Development Stage
			Supervisory Level	High Level		
Zhang et al. [34] (2018)	HKA	P	-	-	Intelligent PID based neural network + time-delay estimation	S
Taherifar et al. [35] (2018)	H	A	-	Adaptive admittance (RBF based gain regulator)	Sliding position control	S, C ($n_h = 1$)
Aycardi et al. [14] (2019)	HKA	A	EEG, EMG, IMU, LRF	-	-	C ($n_p = 8$)
Eguren et al. [36] (2019)	HKA	P, A	-	Variable stiffness impedance control	PD	E
Lyu et al. [37] (2019)	K	A	EMG	-	PD, PID	C ($n_h = 6$)
Chen et al. [38] (2019)	HKA	P	-	-	Fast terminal SMC	S, C ($n_h = 1$)
Chen et al. [39] (2020)	HK	A	-	Impedance	SMC	S, C ($n_h = 1$)
Almaghout et al. [40] (2020)	HK	P,A	-	Admittance	Supertwisting non-singular terminal SMC	S
Chen et al. [41] (2020)	HKA	A	-	Adaptive impedance (Fuzzy logic-based gain regulator)	SMC	C ($n_h = 1$)
Gui et al. [42] (2020)	HK	A	EMG	-	SMC	S, E
Sun et al. [43] (2020)	HK	P	-	-	Adaptive fuzzy decoupling control	S, C ($n_h = 1$)
Yin et al. [44] (2020)	HK	A	EMG	-	-	C ($n_h = 6$)
Tu et al. [45] (2020)	HKA	A	-	Variable admittance	ASMC	C ($n_h = 1$)
Chen et al. [46] (2021)	K	P, A	FSM, FSR	Adaptive Impedance	PD (feedforward compensation)	C ($n_h = 1, n_p = 1$)
Wang et al. [47] (2021)	H	A	SFS	-	Torque control	C ($n_h = 8$)
Andrade et al. [48] (2021)	HKA	A	-	Impedance control	PD control	C ($n_h = 3$)
Narayan et al. [49] (2022)	HKA	P	-	-	Singularity-free terminal SMC	S
Lian et al. [50] (2021)	K	A	-	Adaptive admittance (RNN-based gain regulator)	PD	S
Mokhtari et al. [51] (2021)	HKA	A	-	Impedance	Adaptive high order super twisting SMC	S
Yin et al. [52] (2021)	HKA	-	FSM, FSR, IMU	-	-	C ($n_h = 6$)
Susanto et al. [53] (2021)	K	A	IMU	-	-	C ($n_h = 5$)
Hu et al. [54] (2021)	HK	P	-	-	Adaptive PD	E
Foroutannia et al. [55] (2022)	H	A	EMG, FSR	Impedance	PID	C ($n_h = 7$)
Laubscher et al. [56] (2022)	HKA	A	-	Impedance-SMC	-	C ($n_h = 1$)
Fuentes et al. [57] (2022)	HK	P	EMG, RNN	-	Adaptive non-singular fast terminal SMC	S, C ($n_h = 1$)
Hasan and Dhingra [58] (2022)	HKA	P	-	-	Super-twisting SMC	S
Moodi et al. [59] (2022)	HA	A	-	Variable impedance (Fuzzy logic based gain regulator)	Adaptive neural network	S
Narayan et al. [60] (2023)	HKA	P	-	-	Adaptive backstepping	S
Narayan et al. [61] (2022)	HKA	A	-	Admittance	Computed torque	S
Su et al. [62] (2022)	H	P	-	-	Backstepping	S, E
Wang et al. [63] (2022)	HK	A	EMG (GA-BPNN)	-	SMC	S, C ($n_h = 1$)
Zhu et al. [64] (2022)	HK	A	IMU	Impedance	PID	C ($n_h = 1$)
Roy et al. [65] (2022)	HKA	A	EEG	-	-	S
Qi et al. [66] (2022)	HK	A	FSM, FSR, IMU	-	-	C ($n_h = 5$)
Aljuboury et al. [67] (2022)	K	P	-	-	Model reference adaptive control	S
He et al. [68] (2022)	HK	P	-	-	RBF based adaptive sliding mode	S
Amiri et al. [69] (2022)	HK	P	-	-	Adaptive and swarm fuzzy control	S
Chen et al. [70] (2022)	HK	A	IMU	Variable Admittance	Extended state observer-based backstepping	C ($n_h = 1$)
Zhang et al. [71] (2023)	HKA	A	-	Variable Impedance (RBFNN-based gain regulator)	Fuzzy PID	S, C ($n_h = 1$)
Chen et al. [72] (2023)	HK	A	EMG	Adaptive Admittance	PD	C ($n_h = 6$)
Quiles et al. [73] (2023)	HKA	A	EEG, IMU	-	-	C ($n_h = 3, n_p = 2$)
Di Marco et al. [74] (2023)	HKA	A	EEG, EMG, IMU	-	-	C ($n_h = 10$)
Sun et al. [75] (2023)	K	A	-	Impedance	Model-based control	S, E
Foroutannia et al. [76] (2023)	HK	A	EMG, IMU, FSR	Adaptive-fuzzy impedance	-	C ($n_h = 2$)

H: Hip; K: Knee; A: Ankle; HK: Hip-Knee; HKA: Hip-Knee-Ankle; HA: Hip-Ankle; KA: Knee-Ankle; P: Passive; A: Active.; IMU: Inertial Measurement Unit; FSM: Finite State Machine; FSR: Force Sensing Resistor; EEG: Electroencephalogram; EMG: Electromyography; SFS: Soft Force Sensor; LRF: Laser Range Finder; RNN: Recurrent Neural Network; GA-BPNN: Genetic Algorithm-Backpropagation Neural Network; PID: Proportional Integral Derivative; PD: Proportional Derivative; SMC: Sliding Mode Control; S: Simulation; E: Experimental; C: Clinical; n_h: Number of healthy subjects; n_p: Number of patients.

While several recent publications reviewing exoskeletons exist, only a small portion focuses on the control aspects of lower limb exoskeletons [77,78]. While several of these reviews, such as [79], depend on existing testing parameters such as metabolic cost reduction, others provide a broader categorization with little depth in terms of specifics, such as [80]. A few reviews have focused solely on the employed control strategies while bypassing the implementation details, such as [81]. Most studies span various kinds of control; some choose to focus on the mathematical modeling of the inherent and external dynamics [82], while others include the details of actuator-level implementation [83]. Further, these classifications often occur in similar fashions and use similar terminology for different categories within the same structuring method. For instance, while certain studies define a high-, mid-, and low-level type hierarchy [84], others subscribe to a supervisory level, high-level, and low-level classification terminology [85]. Shi et al. [86] conducted a comprehensive review of human–robot coordination control in lower limb exoskeleton rehabilitation robots. They emphasized the significance of such control systems in providing supplementary training for patients with lower limb walking impairments. They discussed various aspects of human–robot coordination, including modeling, perception, and control. However, this review's scope could be extended to include a deeper understanding of human–robot coordination control at different levels incorporating recent impedance/admittance and servo control schemes. In another recent review by Wang et al. [87] the focus was on developing robotic hip exoskeletons and their potential to both support walking in the elderly and enhance human performance in healthy individuals. However, the study was limited to covering the design, actuation, and control aspects of hip exoskeletons only, and did not delve into the impact of subject-cooperative control schemes in a hierarchical manner. In a separate review, Al-Waeli et al. [88] provided an overview of state-of-the-art gait rehabilitation devices, focusing on various low-level trajectory tracking control methods while omitting their involvement in supervisory and high-level control schemes. Thus, there is room for further research and investigation into integrating these lower-level control methods within a broader hierarchical framework to enhance the overall effectiveness of gait rehabilitation devices.

There is hardly any research available in the literature that has provided a clear and systematic classification of subject-cooperative control strategies for lower-limb exoskeletons. The present review accounts for the hierarchical classification of subject-cooperative control strategies and their implementation in various cases. As this review focuses on different level functions of the control strategy, the classification structure follows a supervisory level, high-level, and low-level framework. A PRISMA-based search methodology was adopted to select the relevant articles, with their deployment, duly correlated with the end usage scenario, understood in terms of its reach across the hierarchy of control elements, schemes, and strategies. To begin with, the elements of control most extensively used across different types of strategies are studied and organized. Next, various strategies and the extent of their reach across the hierarchy are analyzed. A table comprising the therapy modalities and related hierarchy-based control strategies is compiled. Finally, a discussion of emerging approaches and possible opportunities is presented.

2. Search Methodology for Systematic Review

This systematic review followed the PRISMA methodology [89], beginning by identifying relevant databases, including IEEE Xplore, Google Scholar, Scopus, PubMed, and ScienceDirect. The search strategy incorporated combinations from four groups of keywords: subject-cooperative control, gait exoskeleton, lower-limb exoskeleton, and human–exoskeleton interaction; patient-cooperative control, lower-limb exoskeleton, EMG, and EEG; lower-limb exoskeleton, impedance, admittance, robust control, and intelligent control; and a fourth group of keywords encompassing gait exoskeletons, trajectory tracking, shared control, intent recognition, and user intention. The complete systematic process used for selecting and reviewing articles is shown in Figure 1. The initial search yielded a total of 5626 papers from different databases, and an additional search identified 37 papers from other indexing databases. After screening based on title and abstract availability, 343 full-text articles were considered. During the screening, previous versions of articles were excluded if extended versions were published afterwards. Thereafter, exclusion criteria for the full-text articles were applied as follows: published before 2017, without exoskeleton representation, review studies without original work, focused on clinical trials without discussing control aspects, and studies not written in English. Moreover, articles that primarily focused on biomechanics, ergonomics, or human factors were excluded. After applying these criteria, 53 articles were selected for inclusion in the systematic review; these are listed in Table 1. Multiple reviewers were involved in the selection process in order to ensure reliability, and disagreements were resolved through consensus. The selected articles were meticulously analyzed for data extraction, which data were then synthesized and presented in the systematic review, providing comprehensive insights into patient-cooperative control schemes in lower limb exoskeletons.

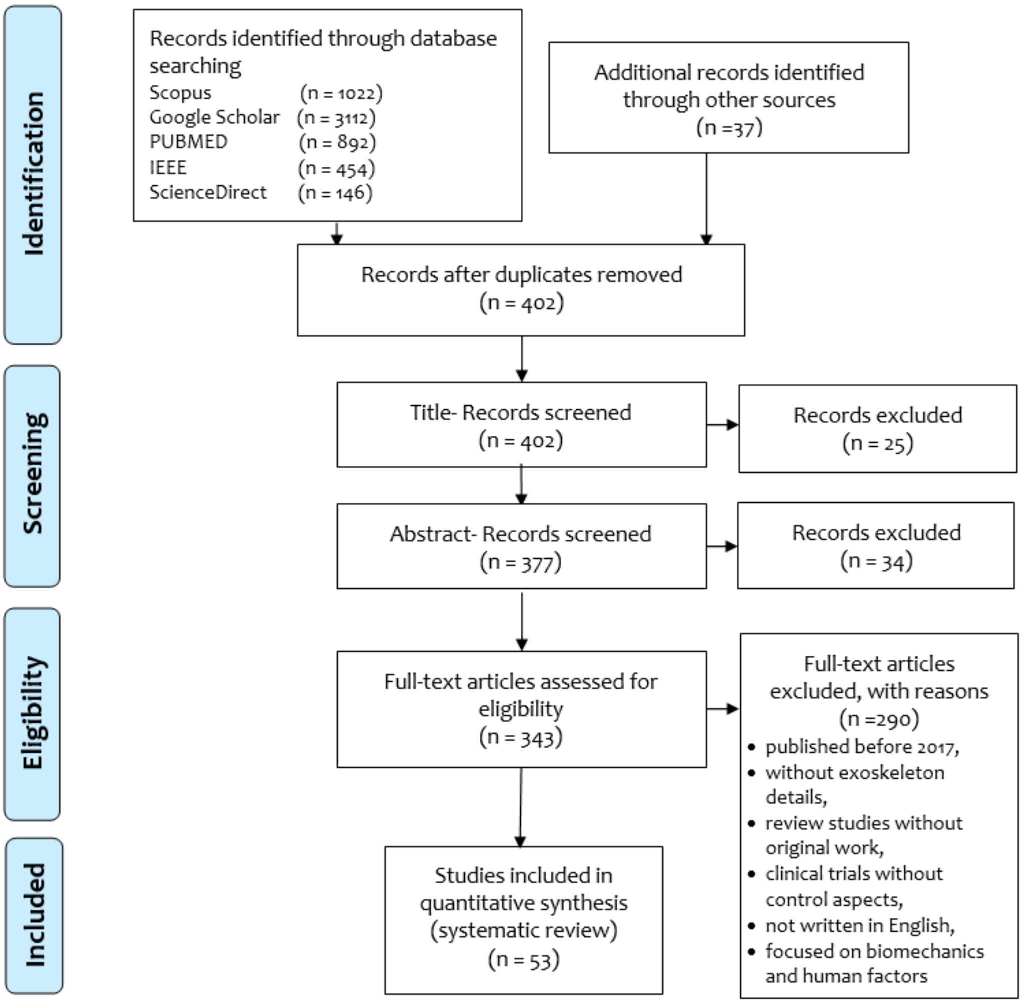

Figure 1. Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) flowchart [89].

3. Hierarchical Classification of Control Strategies

Control techniques regulate the joint torques and position of a coupled subject–exoskeleton system driven by a set of actuators. Considering the crucial role of interlimb coordination in human locomotion, the hierarchical level control scheme is widely recognized for lower-limb exoskeleton robots, encompassing both upper-level and lower-level control. Upper-level control focuses on decision-making algorithms that consider human intent and facilitate "assist-as-needed" interactions between the user and the exoskeleton robot during gait rehabilitation. Conversely, lower-level control pertains to servo control methods that ensure accurate position and torque tracking. Upper-level control can be divided into supervisory control and higher-level control schemes [84]. One such architecture of hierarchical level control is shown in Figure 2. While not all control strategies utilize the entire spectrum of information flow depicted here, most strategies can be accommodated within this framework. As depicted, the data obtained from the environment of the coupled user–exoskeleton system can be divided into two categories: user interaction sensing inputs stemming from the physical interaction between the user and the exoskeleton, and user-generated inputs arising from the user's intent or behavior. These inputs are processed for intent either classification (in supervisory control) or interaction assessment (in high-level control), for which a data acquisition system (DAQ) is used. It is essential to highlight that the gait phase can be updated for interaction assessment in the high-level control by incorporating the information derived from intent classification. Subsequently, a modified gait trajectory is derived based on the desired gait trajectory and the active cooperation of the user. This modified gait trajectory is then controlled by lower-level control schemes utilizing actuator-driven position or torque-based strategies. The joint position sensors acquired via the DAQ can be directly employed as feedback devices in the lower-level control.

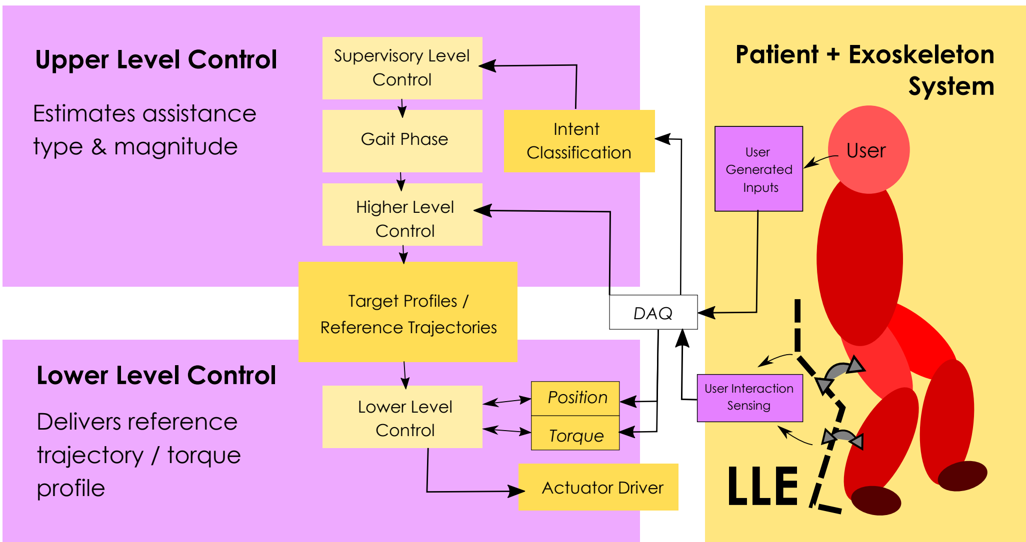

Figure 2. Hierarchical classification of control strategies.

3.1. Upper-Level Control

In the case of robotic exoskeletons, upper-level control refers to the decision-making algorithms that determine the overall set of instructions to be transmitted to the actuation systems, which are controlled by the lower-level control schema. The primary role is to gather information from the user and the environment to identify the intended actions and conditions of use. Based on this information, it decides on the mode of functionality required for the system. In the upper level, the supervisory level is responsible for providing additional feedback to the high-level control and monitoring the operation of the lower-level control schema [84]. The high-level control is responsible for selecting the appropriate functionality mode based on the input received from the user and the environment. This helps to ensure that the exoskeleton system operates safely and reliably while maximizing system performance.

3.1.1. Supervisory Control

The supervisory control layer plays a crucial role in governing the overall behavior of the exoskeleton. It achieves this by performing mode switching between different modes of operation. This switching can be triggered either through intent estimation or by precise inputs provided by the user. The supervisory control layer is responsible for identifying specific phases, such as different gait phases, and determining the type of activity being performed, including walking, fast walking, running, climbing up, climbing down, sitting, standing, and more. After these phases and activities have been identified, the supervisory control layer generates an appropriate instruction set which serves as a joint reference trajectory. This instruction set is transferred to the high-level control, enabling the exoskeleton to align with the desired activity and phase. Inputs for the supervisory control layer can originate from explicit commands provided by the user indicating the desired mode of function and obtained through various sensing instruments to enhance the user experience and simplify the process. Thees include force and motion sensors, muscle data acquisition probes, and brain wave decoding sensors. These techniques estimate the most likely locomotive alternatives associated with motion outcomes. In this way, they streamline the interaction between the user and the exoskeleton system, making it more efficient and user-friendly.

Motion and Force Sensors, sometimes referred to as kinematics or kinetics sensors, are essential instruments that aid in determining the state of the user–exoskeleton system, including segment positions, orientations, and forces of interaction between the user and the exoskeleton and between the exoskeleton and the environment. Motion sensors come in two main types: inertial measurement units (IMU), which combine gyroscopes and accelerometers, and encoders, which are electromechanical devices calibrated to provide specific changes in position or orientation. These sensors are utilized to track joint states, monitor actuator output, and measure the trajectories of exoskeleton segments. They find applications across different levels of control, including in supervisory-level control, high-level control, and lower-level control. Additionally, they can be employed to monitor actuator output. On the other hand, force sensors are typically built as either resistance-based strain gauges (i.e., force sensing resistors (FSR)) or based on the piezoelectric effect. These sensors are crucial in determining various gait features, such as phase, step length, cadence, etc. In particular, certain supervisory control schemes, such as Finite State Machine (FSM) with FSR [30,46,52] and IMU [28,53,64,66], utilize gait phases as additional inputs to the high-level control in combination with reference joint trajectories. For example, Chen et al. [46] implemented an FSM-based supervisory control in which the FSR and encoders (velocity) were employed to discretize the gait cycle into different phases. As depicted in Figure 3, the gait cycle can be divided into four different patterns based on FSR and velocity readings: (1) two phases—stance or swing; (2) three phases—stance, early swing, or late swing; (3) four phases—early stance, late stance, early swing, or late swing; and (4) five phases—early stance, mid-stance, late stance, early swing, or late swing. In another work by Qi et al. [66], a hierarchical support vector machine recognition algorithm was proposed for accurate and reliable locomotion mode recognition in an exoskeleton robot. The proposed algorithm combined the FSM with input signals from IMUs and FSRs to establish a mode transition framework. Experimental results demonstrated high accuracy and low recognition delay rate, indicating the algorithm's effectiveness, efficiency, and potential for wide application in rehabilitation robotics.

Electromyography Sensors (EMG), particularly surface EMG (sEMG), has been employed to implement closed-loop control in exoskeletons for about two decades. Considering the availability of electrical activity information before the intended motion, EMG allows for effective control of lower limb exoskeletons [72,90]. Yin et al. [44] extracted gait cycle duration (GCD) from sEMG signals at various walking speeds, which they then used to program the motion of their exoskeletal system, ultimately showcasing derivation of GCDs from individual muscle contraction. In a study on a progressive assist-as-needed (pAAN) controller for a custom-made lower limb exoskeleton system, Gui et al. [42] employed unsupervised learning of the EMG–torque relationship to estimate a subject's voluntary joint torque without calibration. By adjusting motor control inputs, the pAAN controller enabled precise movement and active participation of subjects during training. Gamified rehabilitation techniques can be deployed on an EMG-enabled apparatus; in one such instance, in Figure 4, Lyu et al. [37] built an EMG-controlled knee exoskeleton to assist stroke patients; the EMG data were processed through a Kalman filter to enable autonomous control of the exoskeleton. Subjects could only use their EMG inputs to control the exoskeleton to play the involved game. In a recent study by Foroutannia et al. [55], a deep learning strategy was proposed using EMG signals to predict the hip joint position and determine the necessary auxiliary force for an exoskeleton robot. Their experimental results demonstrated the effectiveness of the proposed strategy in reducing controller error and supporting the user during walking. In another human-in-the-loop scheme for controlling lower extremity exoskeletons, Fuentes-Alvarez et al. [57] constructed an EMG database and trained a recurrent neural network (RNN) for the classification of EMG to recognize user movements. This information was then sent to a robust lower-level control scheme to offer an effective and precise control system suitable for individuals with a high degree of motor disability.

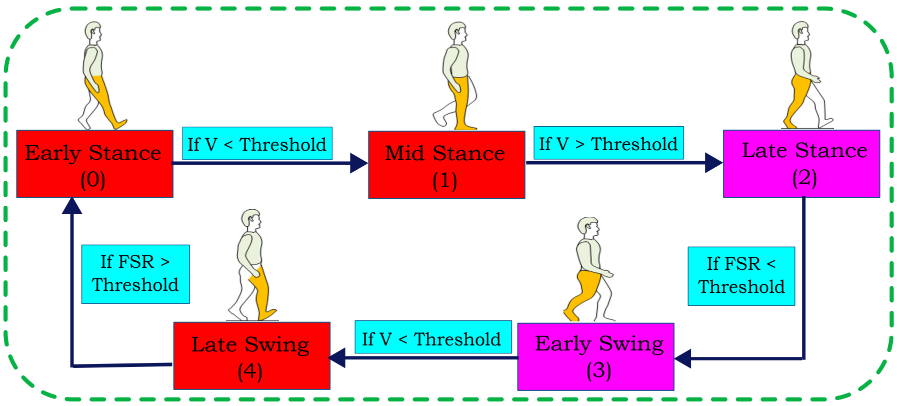

Figure 3. FSM-based supervisory control by Chen et al. [46].

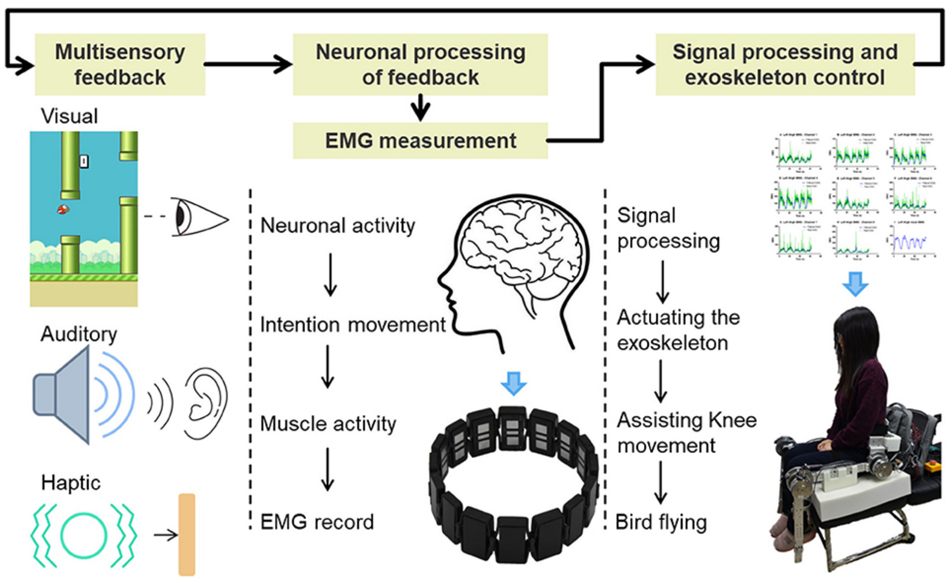

Figure 4. EMG-based rehabilitation process by Lyu et al. [37].

Electroencephalography Sensors (EEG) are a non-invasive method to capture brain activity, and exhibit considerable advantages in cost, compatibility, and temporal resolution compared with other brain–machine interface methods such as functional magnetic resonance imagining (fMRI) and magnetoencephalogram (MEG). However, they provide low spatial resolution, and generally have a weak signal with a poor signal-to-noise ratio [91]. Extensive signal processing is required to extract the rhythms of cortical electrical activity.

EEG signals are used to determine user intent and direct the exoskeleton system accordingly. In one such instance, Roy et al. [65] focused on developing a real-time guideline for controlling an assistive robotics device using motor imagery EEG signals. They proposed a novel feature extraction method combining the power of cross-correlation and spectral entropy. Machine learning algorithms were employed for signal classification, achieving high average accuracy. A lower limb exoskeleton device was designed and controlled using the classified EEG signals, resulting in satisfactory exoskeleton motion. In a recent study by Quiles et al. [73], a brain–machine interface was developed to detect the intention to stop in response to unexpected obstacles. They utilized two consecutive convolutional networks to discern the intention to stop and correct false detections. The methodology showed improved results in both treadmill and exoskeleton experiments, with reduced false positives and improved detection rates. In addition, they applied and validated transfer learning techniques for potential applications in patients with spinal cord injuries.

Moreover, the combination of the above-mentioned sensing modalities at the supervisory level allows for the estimation and syncing of human intent with muscle activities to enable gait timing. In the CP Walker by Aycardi et al. [14], human–robot interaction is carried out using a Multimodal Human–Robot Interface (MHRI) which includes an EEG unit, EMG system, IMU, and Laser Range Finder (LRF) to measure the gait cycle and control the device accordingly. However, the abnormal gait patterns of subjects with CP make it difficult for the supervisory-level controller to detect or predict gait phases. This implies that custom development of gait trajectories suited to specific users becomes necessary for practical functioning. Such combinations can be used for understanding motor learning by mapping brain activities with gait timings during rehabilitation. In another work on leveraging multimodal sensory interfaces, Di Marco et al. [74] aimed to quantify the impact of a single session of robot-aided gait training on brain activity and motor learning. They recorded and analyzed EMG, IMU, and EEG data before and after gait training. The results showed changes in walking patterns and modulation of cortical activity in the motor, attentive, and visual cortices, indicating an effect of robot-aided gait therapy on neuromuscular and brain activity. These findings contribute to understanding human–machine interaction and motor learning, potentially enhancing the development of more effective exoskeletons for assisted walking.

3.1.2. Higher-Level Control

Because effective rehabilitation requires patient participation, high-level control strategies exploit the admittance/impedance model, which offers active participation to the users in the gait training by leveraging their residual muscle movement under the aspect of "assist-as-needed" (i.e., ALEX II by Lenzi et al. [13], P-LEGS by Eguren et al. [36]). It is crucial to understand the essential antagonistic components of this level of control, i.e., admittance and impedance. In the last five years, active research on the impedance/admittance controller for the gait exoskeletons has been started [32,35,40,45,51,61].

Admittance control is used extensively in user–robot interaction environments and works on altering motion output based on measured forces. Forces and moments are transformed into necessary positions/orientations desired for the end effector. In addition to the supervisory-level sensors, the coupled exoskeleton–human interaction forces can be measured using disturbance observers [41] and force sensors [45,47]. A spring–mass–damper mathematical model can be used to realize interaction forces in simulated settings as an effect of soft coupling between subject and exoskeleton [40,45]. As shown in Figure 5, Tu et al. [45] proposed an admittance control based on the standard and measured interaction torque where interaction between the human and the exoskeleton is measured using force sensors. Later, invoking the desired human gait trajectory, the admittance controller updates the reference trajectory as an input to the low-level control. Similarly, in a more simplified way, Almaghout et al. [40] presented an admittance control algorithm to reduce undesired interaction torques between a knee/ankle rehabilitation robot and patient to ensure a safe therapy session. Recently, soft computing and deep learning techniques have become very popular, as they can account for the different assistance/resistance levels of patients. Examples include fuzzy logic in [25,35] and a recurrent neural network in [50]. Lian et al. [50] exploited the interaction torque as an input for optimizing admittance parameters using a Jordan recurrent neural network (JRNN) (see to Figure 6). In a recent study by Chen et al. [70], a variable admittance controller was designed to reduce the human–exoskeleton interaction torque based on the gait prediction uncertainties, which were estimated using a deep Gaussian process. However, such techniques include the random selection of hyperparameters in the network, which increases the computational complexity of the overall control process.

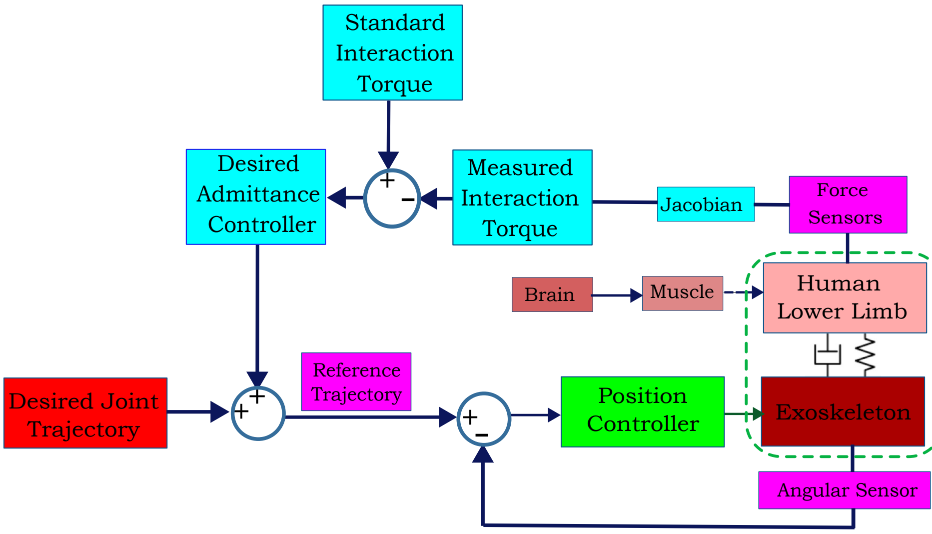

Figure 5. Admittance control architecture proposed by Tu et al. [45].

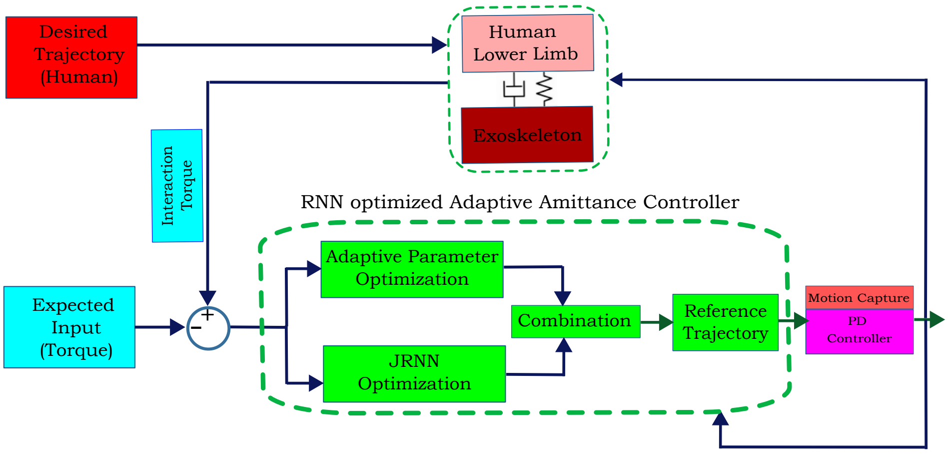

Figure 6. Jordan RNN-optimized admittance control framework by Lian et al. [50].

Impedance control, the inverse of admittance, is used in user–robot interaction where robots physically interact with their surroundings and deliver adjustments in force/torque outputs based on measured displacements or deviations from motion trajectories [92]. Mokhtari et al. [51] obtained the optimal impedance parameters; however, they did not consider the varying impedance model, as in the case of the natural environment during active-assist gait rehabilitation. Chen et al. [39] transformed the angle dynamics equation of a lower limb exoskeleton into a Cartesian coordinate system to calculate the end contact force and design an impedance control strategy with a disturbance observer suitable for non-linear and strong coupling characteristics. In an experimental study on a 6-DOF exoskeleton, Andrade et al. [48] proposed a high-level finite state trajectory tracking impedance control and tested it with three adult male subjects. Laubscher et al. [56] proposed a novel hybrid controller for safe human–robot interaction combining impedance control and sliding mode control (SMC). The controller consisted of inner-loop and outer-loop controllers for feedback linearization and trajectory tracking, respectively. A walking experiment with a lower-limb exoskeleton was used to validate the controller's effectiveness, showing a statistically significant reduction in feedback torque magnitudes by 7.9% while maintaining similar gait patterns and joint angles, demonstrating its potential as a safer alternative to impedance control. Recently, as shown in Figure 7, Sun et al. [75] presented an impedance control for a gait exoskeleton driven by series elastic actuators (SEA). They designed an SEA structure with negative stiffness to achieve vibration isolation in the low-frequency excitation region. Moreover, in the case of variable impedance control, there has been a recent surge in the popularity of soft computing and deep learning techniques for enabling various levels of assistance and resistance in patient care. These techniques include fuzzy logic [59,76] and fuzzy-based radial basis function networks [71]. Zhang et al. [71] proposed a fuzzy radial-based impedance controller for the human–machine interaction problem in lower extremity rehabilitation exoskeletons. The proposed controller consisted of an inner-loop fuzzy position control module for trajectory tracking and position adjustment and an outer-loop impedance control module for regulating impedance parameters and compensating for uncertainties. Simulation and hardware tests demonstrated the effectiveness of the proposed controller in achieving coordinated and smooth movements between the subject and the exoskeleton system.

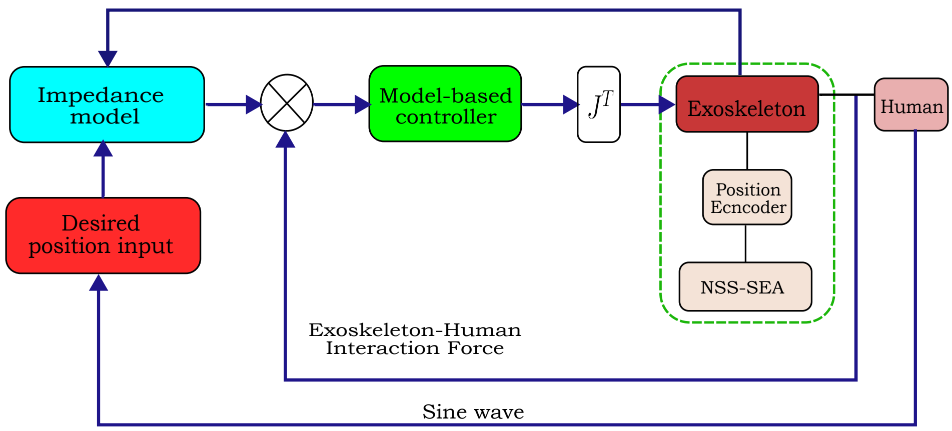

Figure 7. Impedance control by Sun et al. [75] (J^T denotes Jacobian transpose and NSS-SEA refers to the negative stiffness structure–series elastic actuator).

3.2. Lower-Level Control

Low-level torque/position control attempts to track a reference torque/position based on the actuator's electric current as the input state [84,85]. During the initial stages of therapy, position control guarantees that the exoskeleton robot can track the desired gait trajectory, with potentiometers used to measure movement information. Position-based control can be achieved in a multitude of fashions. In the existing research, predetermined gait tracking control is considered the fundamental element of all control strategies implemented in exoskeleton systems. In this context, the motion of the limb joints can be recorded through motion capture experiments (for example, PID control in EXPOS by Kong and Jeon [93], fuzzy control in ABLE by Mori et al. [94], PD control in CUHK-EXO Chen et al. [26]). However, in practice predefined gait tracking control for exoskeletons is insufficient to achieve gait trajectory due to the parametric perturbations and unwanted interference arising from intricate mechanical arrangements, sophisticated motion paths, and human engagement. Therefore, different robust and intelligent control schemes have been explored in the last five years to address the limitations of classical control schemes.

3.2.1. Robust Control

Robust gait tracking control allows the exoskeleton system to maintain stability and performance despite uncertainties or disturbances. Exoskeletons interact with the human body, introducing uncertainties such as varying physiological conditions, environmental changes, and unpredictable user inputs. Robust control techniques such as adaptive or robust feedback control can compensate for these uncertainties, ensuring that the exoskeleton operates reliably and safely. By incorporating robust control strategies the exoskeleton can adapt to changing conditions and disturbances, providing consistent and effective assistance or resistance to the user during rehabilitation and assistance tasks [27,31,38,69]). For instance, Amiri et al. [69] developed an adaptive and swarm-fuzzy logic control for a 4-DOF exoskeleton intended to aid in regaining limb function in cases of hemiplegia. In the experimental results, the proposed control strategy proved to be an efficient real-time control method for joint trajectory tracking. For a knee exoskeleton, Khamar and Edrisi [31] proposed a control method based on a backstepping sliding control combined with a nonlinear disturbance observer (NDO). The NDO reduced the impact of uncertainties and external disturbances in the system model, while the backstepping sliding approach, optimized using a genetic algorithm, improved control performance. The proposed controller demonstrated superiority over recent methods, reducing disturbance rejection time, chattering, and tracking error. Chen et al. [38] proposed a control strategy combining active disturbance rejection control with fast terminal SMC to improve the tracking behavior of a gait exoskeleton. Simulations and experiments demonstrated that the proposed strategy was able to outperform contrast control schemes in tracking performance, achieving higher precision and faster response in the exoskeleton system. Hu et al. [54] proposed an adaptive control scheme to deal with an uncertain 2-DOF lower-limb rehabilitation device. Recently, Aljuboury et al. [67] designed a model reference adaptive control (MRAC) for a knee exoskeleton. Computer simulations demonstrated that the MRAC with a nonlinear observer offered better robustness and promising trajectory tracking, with fewer estimation errors compared to classical MRAC and MRAC with an adaptive disturbance observer.

Furthermore, to address chattering phenomena, slow convergence, and sensor drift in existing SMCs, researchers have updated different attributes and tested preliminary designs of gait exoskeleton robots (for example, non-singular terminal SMC by Narayan et al. [49], adaptive non-singular fast terminal SMC by Han et al. [33], and super-twisting SMC by Hasan and Dhingra [58]). In other works on robust position control, Yang et al. [29] proposed an SMC with a second command filter-aided backstepping to avoid the “explosion of terms” problem. Fuzzy logic was used to suppress chattering behavior while estimating the uncertainties. Most existing hierarchical control schemes exploit non-robust position control in the inner loop to track the modified gait trajectory. To address uncertain dynamics and external disturbances, sliding surface-based position control schemes have recently been used to track the reference trajectory of human–robot interaction [31,45]. However, the problem of fast convergence of error states has not been considered. Addressing this challenge, Almaghout et al. [40] proposed a super-twisting non-singular terminal SMC to perform the desired training tasks with finite-time convergence of the error states. However, information on selecting the admittance parameters is not evident. In other works on robust inner loop position control, Mokhtari et al. [51] designed an adaptive high-order super-twisting SMC for a lower limb exoskeleton robot. Although this kind of high-order sliding mode control reduces the chattering effect, it requires high controller gain values to compensate for uncertainties and disturbances [95]. Such high gain values can degrade the stability of the system.

In addition to SMC, backstepping control is another well-known nonlinear control scheme that can guarantee trajectory tracking with global regulation [96]. The design of backstepping control is a step-by-step recursive process that inherently establishes the stability criteria using the appropriate Lyapunov candidate functions. In work by Su et al. [62], a backstepping-based nonlinear controller was developed for hardware-in-loop simulation of a 1-DOF hydraulic hip-knee exoskeleton. A conventional backstepping controller cannot ensure this system's robustness against parametric and non-parametric uncertainties. Therefore, adaptation laws have been used in the literature with backstepping techniques, termed adaptive backstepping control, to deal with uncertain dynamics and external disturbances [96,97]. However, such control designs pose certain limitations, such as overparameterization [98], explosion of terms [99], and larger magnitudes of the control signals [100]. A robust adaptive backstepping control for a 6-DOF pediatric exoskeleton system, proposed by Narayan et al. [60], is shown in Figure 8, where the tracking error and its derivatives are used to design a virtual controller and adaptive law. Nonetheless, solving regression matrices is a computationally expensive process [60,97]. Therefore, researchers nowadays are working on merging sliding mode and adaptive backstepping control, i.e., the adaptive backstepping sliding mode control, to obtain the respective advantages of both together [101].

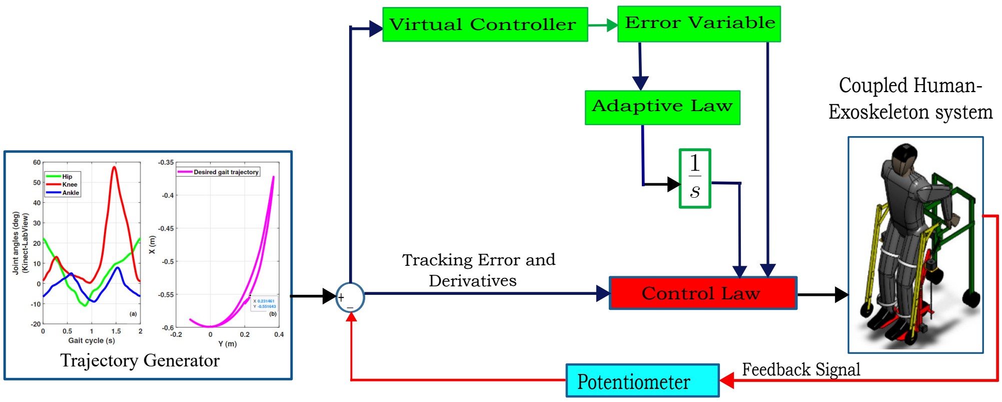

Figure 8. Robust adaptive backstepping control for a pediatric exoskeleton system by Narayan et al. [60].

3.2.2. Intelligent Control

In recent years, there has been increasing interest in the application of robust intelligent control strategies to mitigate the uncertain effects of exoskeleton devices by leveraging their effective approximation capabilities [34,43,63,102]. Zhang et al. [34] added a neural network and time-delay estimation technique to a model-free based intelligent PD (iPD) controller, finding that the proposed controller achieved a more stable and effective tracking trajectory compared to a PD controller as well as to neural network-based and model-free based iPD controllers. Using a lower extremity exoskeleton system, Narayan and Dwivedy [102] developed a neuro-fuzzy compensated PID control strategy for passive gait rehabilitation. This control strategy was implemented on a pediatric exoskeleton and compared to PID control, showing a 40% reduction in the root mean square error for tracking the healthy gait trajectory. The robustness of the proposed controller was demonstrated through variations in lower limb masses and external disturbances, and low settling time values in both directions evidenced its fast convergence. Working on the decoupled control strategy, a reduced-order adaptive fuzzy approach was designed by Sun et al. [43] and tested on a gait exoskeleton system. Wang et al. [63] proposed a periodic event-triggered SMC scheme for lower-limb exoskeletons in a human–robot cooperation scenario. They utilized a genetic algorithm–backpropagation neural network to estimate the wearer's motion intention using EMG signals. The effectiveness of the proposed control method was validated through comparative simulations and experimental analysis. He et al. [68] investigated a robust SMC with an RBF network compensator for a compliant tendon sheath-driven gait exoskeleton, which they found to offer a reduction in the frictional effects resulting from the actuation system. The proposed controller showed fast, stable, and accurate control performance despite uncertainties. Intelligent techniques such as neural networks and neuro-fuzzy approaches have excellent approximation capabilities, which is beneficial for the classical PID control technique used to form a robust control scheme. However, in all such intelligent techniques the initial selection of network hyperparameters is an iterative and cumbersome task that is required for effective model identification.

4. Discussion

As outlined in Table 1, in the last five years a wide range of control strategies and techniques have been applied to lower-limb exoskeleton systems. These studies can be classified into different hierarchical levels focusing on various aspects of control. However, there has been limited research on integrating supervisory control strategies and robust gait tracking control at the lower level, and vice versa. In the future, there is potential to enhance the control schemes of lower limb exoskeletons by incorporating patient cooperative control strategies. These strategies aim to gather information directly from the user's muscles and brain using techniques such as EMG, EEG, and neural implants such as Neuralink. Tapping into user intent enables more natural and intuitive interaction between the user and the exoskeleton device. While recent research has made significant advancements in biosignal processing capabilities for patient-cooperative control, though there remains a benchmark problem in accurately estimating gait phases when using only supervisory control strategies, particularly for individuals with abnormal gait patterns [85]. This highlights the need for further advancements in this area to improve the effectiveness of lower limb exoskeletons for rehabilitation purposes. Overall, future research efforts should focus on bridging the gap between supervisory control strategies and robust gait tracking control while leveraging patient cooperative control schemes to enhance the interaction and performance of lower limb exoskeleton systems.

Another noteworthy point is that most studies on exoskeletons have exploited the impedance control scheme in the high-level control approach. As impedance control requires real-time information on the reference torque using expensive sensors, it is possible to explore the admittance control scheme with a robust gait tracking control scheme to enable a human-in-the-loop cooperative control approach. One important aspect of the cooperative control scheme is the achievement of variable impedance/admittance parameters over a gait cycle to closely mimic the real-time changing admittance of biological leg, which offers additional safety benefits along with the flexibility to participate in therapeutic training. As there are very limited works on variable impedance/admittance models, novel designs based on intelligent algorithms could be designed further in a cooperative control scheme. The benefits of applying such cooperative control in the presence of sudden interaction reflexes could be further investigated for gait exoskeleton systems.

The development stages (simulation, experimental, and clinical) of control-equipped exoskeleton devices are shown in the last column of Table 1 and visually represented in Figure 9a,b. The 'clinical' settings are inferred to be those studies in which a cooperative control-aided device was tested with healthy subjects or/and patients suffering from neurological diseases. On the other hand, 'experimental' signifies those studies in which the device was tested with no human involvement, while 'simulation' refers to studies in which cooperative control schemes were validated for a virtual model of a device. Following the clinical information gathered through this review and presented in Table 1, it is notable that 56.6% of subject-cooperative control schemes for the lower-limb exoskeletons were validated in clinical settings rather than simulation (30.2%) or experimental ones (13.2%) (Figure 9a). However, as shown in Figure 9b, it is pertinent that a significant portion of these clinical studies (76.4%) considered healthy subjects rather than patients when validating control-aided exoskeleton systems for gait training. Therefore, there is significant scope for researchers to carry out further clinical trials with actual patients suffering from neurological diseases in order to prove the efficacy of gait exoskeletons among potential users.

In view of the need for contactless healthcare recently highlighted by the COVID-19 pandemic, there is a need for advanced patient cooperative control schemes in lower-limb exoskeletons. To address this, an emergent strategy is required to merge supervisory and high-level control strategies that can adapt to the user's behavior. These control strategies should consider the patient's progress, assess their level of participation, and track their capabilities in order to dynamically adjust the robotic control parameters. The hierarchical classification methodology used to study control strategies may face limitations in capturing the full scope of these adaptive control approaches. It is becoming evident that a simple level-wise division may not be sufficient to encompass the wide range of control strategies that can be employed in lower limb exoskeletons. A more comprehensive classification scheme is needed, one that combines hierarchical distinctions with elemental considerations, in order to provide a more exhaustive and structured overview of the various control approaches used in lower limb exoskeleton systems. Such a holistic and integrated classification approach would facilitate a deeper understanding of the interactions between different control levels and their impact on the overall performance and adaptability of lower limb exoskeletons. By adopting a combined mapping of hierarchical and elemental distinctions, a more comprehensive and nuanced framework for organizing and evaluating control strategies can be established.

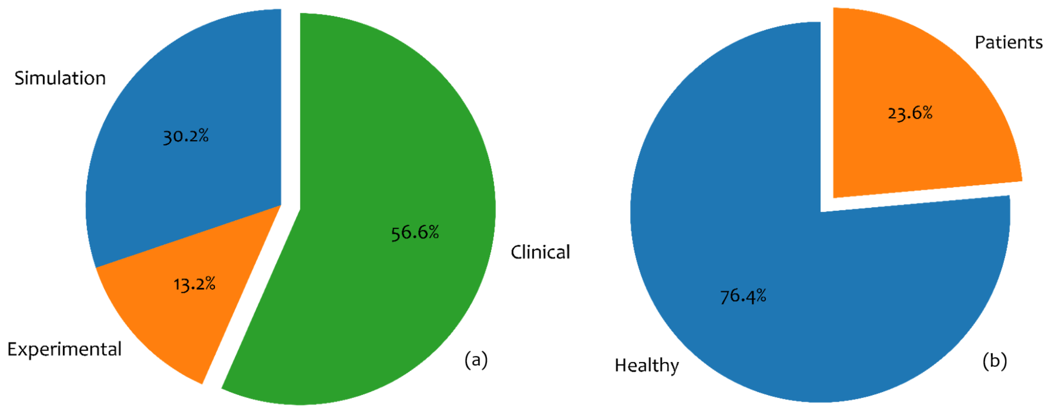

Figure 9. Development stages: (**a**) relative percentages of simulation, experimental, and clinical studies and (**b**) relative percentages of clinical studies with healthy subjects and patients.

5. Conclusions

In this article, a systematic overview of subject-cooperative control strategies for gait exoskeletons has been presented. The PRISMA statement is included to depict the inclusion and exclusion criteria of the selected papers in this systematic review. First, this review has covered the basics of lower-limb exoskeleton systems and the related rehabilitation modes. A hierarchical classification has been presented in the text as well as in tabulated form to represent existing control strategies in supervisory level, high-level, and low-level controllers. The different methods used to estimate the level of subject cooperation in different control schemes have been highlighted as a means to improve the knowledge base included in the review. The future research scope and clinical developments of patient-cooperative control in gait exoskeletons have been discussed in order to provide an understanding of the latest research. In light of the current pace of innovation in assistive technologies, this review can be utilized to provide an organized overview of future cooperative strategies.

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Conflicts of Interest: The authors declare that this research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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