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Review

Sliding Mode Control Application in Knee and Lower-Limb Exoskeletons: A Review

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Abstract

This review systematically surveys Sliding-Mode Control (SMC) strategies applied to knee and lower-limb exoskeletons with direct knee-related control or evaluation, emphasising research published over the last decade (2015–2025). The paper first outlines key control challenges arising from nonlinear joint dynamics, external disturbances, sensor feedback, and uncertainties in human–robot interaction. The review then analyses 126 unique studies, including peer-reviewed journal articles and full conference papers, covering classical SMC, higher-order formulations, observer-based architectures, intelligent adaptive schemes, and optimisation-enhanced approaches. Beyond tracking accuracy and chattering behaviour, the review considers practical aspects relevant to wearable rehabilitation systems, including sensing requirements, real-time implementation, patient-specific adaptation, and human–robot interaction. These aspects highlight current methodological trends, practical limitations, and the gap between control performance and real-world rehabilitation use. The review aims to support the development of more robust, safe, and practically deployable control frameworks for knee and lower-limb exoskeletons in rehabilitation applications.

Keywords: sliding-mode control; lower-limb exoskeletons; knee orthosis; human–robot interaction; wearable rehabilitation

1. Introduction

Wearable robotic devices, often called exoskeleton robots (ERs), are increasingly important in rehabilitation medicine, assistive technology, and mobility enhancement for individuals with motor impairments [1]. Lower-limb exoskeletons are particularly significant because they restore gait function and provide external support to individuals affected by stroke, spinal cord injury, or muscular disorders [2,3]. These devices integrate actuators, sensors, and control algorithms to replicate human motion and facilitate rehabilitation training [4]. In wearable rehabilitation systems, controller effectiveness also depends on how well it uses sensor feedback, operates in real time, and responds to changes in the user's movement and physical condition [5,6]. Within the lower limb, the knee joint plays a central role in weight-bearing, stability, and locomotion. Consequently, dedicated knee orthoses and multi-joint lower-limb exoskeletons often incorporate knee actuation to support proper gait generation and safe physical interaction [7–10]. Such devices are designed not only to assist patients with impairments, including patellar pain or ligament deficiencies, but also to enhance muscular output during rehabilitation exercises [11–13]. Evidence from

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knee-bracing studies suggests that external knee support can influence knee-extension strength [14]. However, these findings do not directly support improved gait symmetry or reduced user effort during exoskeleton-assisted rehabilitation. Despite these benefits, designing effective knee exoskeletons remains challenging. The knee exhibits highly nonlinear, time-varying, coupled dynamics influenced by soft-tissue behaviour, external disturbances, and patient-specific variability [15]. Moreover, the interaction between the human user and the robotic joint introduces uncertainties in torque demand, joint stiffness, movement intention, and load distribution. For wearable applications, these challenges are further affected by sensing accuracy, measurement noise, computational limitations, and the need to adapt assistance to individual users [5,6,16].

To address these complexities, a wide range of control strategies has been explored in both single-joint and multi-joint lower-limb devices, including proportional–derivative (PD) control [17] model reference adaptive control (MRAC) [18,19], cascaded proportional–integral–derivative (PID) schemes [20], impedance control [21,22], torque-based methods [23–26], nonlinear impedance reduction control (IRC) [27], flow control [28], and sliding-mode control [29]. However, many traditional controllers struggle under unmodeled dynamics, time-varying disturbances, or rapid changes in user behaviour, limiting their effectiveness in real-world rehabilitation settings. Sliding-Mode Control has therefore emerged as a desirable method due to its robustness against model uncertainties and external disturbances [29].

By enforcing system trajectories onto a predefined sliding surface, SMC ensures stable tracking despite variations in system parameters. However, classical SMC is also known for producing chattering, high-frequency oscillations that may increase energy consumption, cause mechanical wear, and reduce user comfort [30]. To address this, advanced forms of SMC have been proposed, including second- and higher-order methods [31] boundary layer approaches [32] and fractional-order formulations [33]. Further extensions, such as a terminal [34] and integral SMC [35], as well as hybrid designs incorporating adaptive backstepping [36], fuzzy logic and neural networks [37] and optimisation techniques [38] have demonstrated potential in enhancing tracking accuracy, adaptability, and safety in human–robot interaction.

Given the rapid growth of SMC-based strategies in knee-related applications, including specialised knee orthoses and lower-limb exoskeletons with knee-joint control, this paper reviews recent and current advancements in SMC-based control strategies for knee and lower-limb exoskeleton systems. Beyond comparing control performance, this review considers how reported SMC approaches integrate sensing, real-time or hardware implementation, adaptive and intelligent methods, and human–robot interaction in rehabilitation applications. The review also examines their practical limitations and identifies areas that require further development to support safe, wearable, and patient-oriented knee and lower-limb exoskeleton systems. Existing reviews have addressed lower-limb exoskeleton control, rehabilitation robotics, or sensing technologies; however, they have not jointly examined knee-related SMC strategies in terms of tracking performance, chattering mitigation, sensing requirements, real-time implementation, and human–robot interaction. The present review addresses this gap through systematic study selection, within-study RMSE synthesis, a dedicated chattering-mitigation taxonomy, and implementation-oriented analysis.

2. Literature Review

A systematic literature search was conducted to identify studies investigating SMC and SMC-based strategies for knee and lower-limb exoskeleton systems. The search was restricted to publications from January 2015 to December 2025. The final searches of Scopus, IEEE Xplore, and ScienceDirect were conducted on 5 October 2026. No supplementary

searches were conducted using Google Scholar or other sources, and no additional records were introduced through supplementary searching.

Four supplementary tables provide additional supporting information for this review: Supplementary Table S1 presents the paired RMSE comparisons and engineering-focused appraisal; Supplementary Table S2 provides the database-specific search strategies; Supplementary Table S3 contains the study-selection register and source provenance; and Supplementary Table S4 documents the chattering-mitigation classification.

The search strategy combined terms related to the robotic system and control method, including "knee exoskeleton", "knee orthosis", "lower limb exoskeleton", and "lower-limb exoskeleton" with terms such as "sliding-mode control", "SMC", "super-twisting", "higher-order sliding mode", "terminal sliding mode", "fractional-order sliding mode", and "adaptive sliding mode". Database-specific adaptations of the search strategy were used where required. The reported database-specific Boolean search strings, search fields, filters, and search dates are provided in Supplementary Table S2.

The searches identified 307 records: 141 from Scopus, 57 from IEEE Xplore, and 109 from ScienceDirect. After removal of 50 duplicate records, 257 unique records remained for title and abstract screening.

2.1. Inclusion and Exclusion Criteria

Studies were eligible if they: (1) were published in English between 2015 and 2025; (2) were peer-reviewed journal articles or full conference papers; (3) investigated a knee exoskeleton/orthosis or a lower-limb exoskeleton with direct knee-related modelling, control, trajectory-tracking, torque, or experimental results; (4) employed SMC or an SMC-based variant as part of the proposed control strategy; and (5) provided simulation and/or experimental validation.

Studies were excluded if they were reviews, editorial material, proceedings-only records, book chapters, theses, or non-peer-reviewed preprints; focused exclusively on upper-limb, hip-only, or ankle-only systems; mentioned SMC only as a benchmark or in the background; did not provide direct knee-related evidence; or did not provide an appropriate simulation and/or experimental validation of the proposed control strategy.

2.2. Study Selection

The study-selection process is summarised in Figure 1. The authors conducted title and abstract screening, full-text eligibility assessment, and data extraction using the predefined inclusion and exclusion criteria. Uncertain cases were re-assessed against the eligibility criteria and source publications before a final decision was made.

After title and abstract screening, 113 records were excluded, leaving 144 reports for full-text retrieval. Four reports could not be retrieved, and 140 full-text reports were assessed for eligibility. A further 13 reports were excluded, leaving 127 eligible reports. One pair of companion publications was linked to a single underlying study to avoid double counting. The final synthesis therefore comprised 126 unique studies.

Supplementary Table S3 provides the report-level study register, including bibliographic information, report-to-study mapping, companion-report identification, and source provenance.

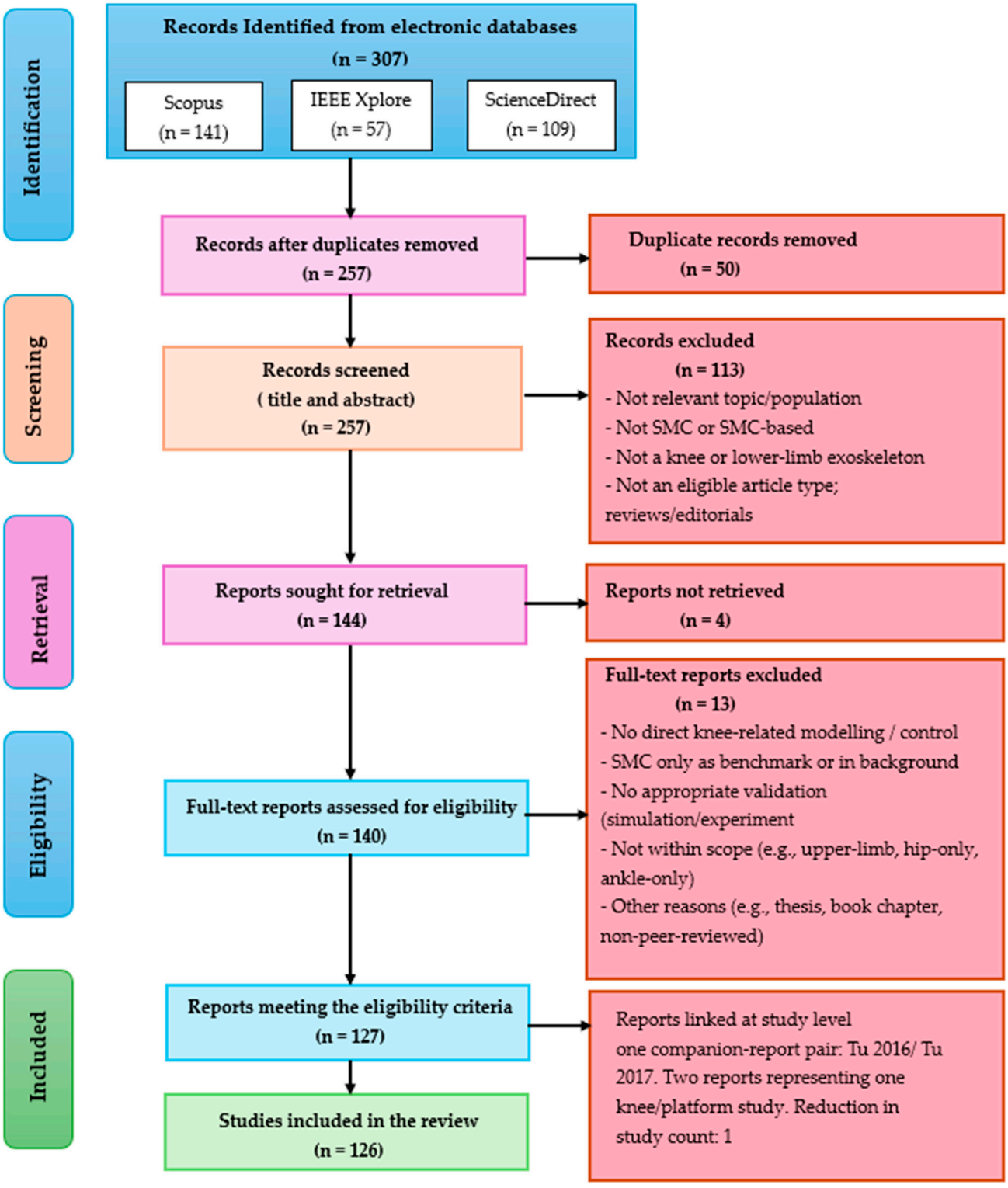


Figure 1. PRISMA flow diagram of the literature search and study selection process.

3. Overview of Control Strategies in Knee and Lower-Limb Exoskeletons

Control strategies for knee orthoses and lower-limb exoskeletons have evolved significantly to support rehabilitation, enhance mobility, and ensure safe human–robot interaction. Early efforts often relied on classical control techniques, such as PID or PD controllers, in orthotic devices [39–41]. However, these classical PID methods face challenges when applied to more complex exoskeletons with significant nonlinearities, reducing stability and position-

control accuracy [42,43]. To address these limitations, impedance- and admittance-control approaches became popular for improving transparency and compliance between the user and the orthosis. Several studies implemented active impedance control and impedance shaping to enhance torque control and responsiveness [22,23,27]. Admittance-based strategies have also been widely used, including those incorporating neural networks for real-time gait adaptation [17,44,45], contributing to more personalised rehabilitation experiences. Beyond classical methods, researchers have developed advanced adaptive and model-based controllers that dynamically tune system behaviour based on patient-specific conditions. Examples include adaptive force-position control for flexible actuators [46], model reference adaptive control for human-in-the-loop systems [47], and hybrid multi-loop architectures that combine active disturbance rejection (ADRC) with sliding mode and PD controllers to enhance robustness under patient-specific disturbances [48]. Another line of research has focused on robust control techniques that maintain stability and performance despite modelling errors, unexpected disturbances, and variable human–robot interaction forces. Methods within this category include H_∞, μ-synthesis, adaptive robust control, and various forms of sliding-mode control [49–55]. Other researchers have proposed bounded torque control laws [56] and anti-disturbance frameworks to stabilise the interaction while avoiding actuator saturation [57]. Intelligent and hybrid methods have also emerged, incorporating fuzzy logic [58–60], RBF neural networks [17,61,62], and reinforcement learning structures for online adaptation to patient movement patterns [63].

Additionally, several supporting frameworks have been explored to enhance overall system performance. These include human intent estimation based on EMG, gait phase detection, or user effort levels, as well as assist-as-needed (AAN) paradigms that modulate the level of assistance according to patient capability [64–66]. Mechanical design studies, such as those exploring isostatic and lightweight orthoses [67–70] have further supported control strategies by enabling more precise torque application and better user comfort. Several papers also emphasised trajectory planning and stability guarantees under constraints [71,72] while additional work has investigated real-time control implementation through optimised computational pipelines, stiffness modulation mechanisms [73], and hierarchical or multi-loop control architectures [48,74].

These developments show that controller design in wearable knee and lower-limb exoskeletons is closely linked to sensing, embedded computation, actuator dynamics, and human–robot interaction. Sensor signals such as joint position and velocity, interaction force, electromyography, and gait-phase information can provide feedback on both the user and the device. At the same time, adaptive and intelligent controllers can use this information to adjust the level of assistance. However, these approaches also introduce practical challenges related to measurement noise, sensor reliability, computational demand, actuator response, and real-time implementation.

Table 1 shows the progression from classical PID/PD control toward adaptive, robust, intelligent, and hybrid control architectures. Despite this progress, maintaining accurate and stable performance under modelling uncertainty and variable human–robot interaction remains a major challenge. Soft-tissue deformation, joint misalignment, actuator friction, sensor noise, and changes in user effort introduce uncertainties that can degrade controller performance. Sliding-Mode Control (SMC) is therefore particularly attractive because it is inherently robust to modelling errors and external disturbances.

Table 1. Summary of control strategies for knee-joint control in lower-limb exoskeletons.

Control Strategy	Advantages	Limitations	References
Classical (PID/PD) Control	Easy implementation, basic trajectory control.	Poor performance with nonlinearity, sensitive to disturbances, not ideal for human–robot variability.	[39–43]
Impedance Control	Improves transparency, compliance and torque control.	Performance degrades with strong nonlinearities, is sensitive to misalignment and soft-tissue effects, and requires complex tuning.	[22,23,27]
Admittance Control	Enables real-time gait adaptation and personalised rehabilitation.	Requires accurate sensors, is sensitive to noise, and may become unstable under fast dynamics.	[17,44,45]
Adaptive/Model-Based Control	Tuning system behaviour to individual patient needs, robustness against disturbances.	High computational cost, requires model knowledge, may overfit or adapt slowly in human use.	[46–48]
Robust and Nonlinear Control (including SMC, H∞, μ-synthesis)	Designed to maintain performance under model uncertainties and external disturbances, with high precision and strong disturbance rejection.	May cause high control effort; robust methods often involve complex tuning and are limited to matched uncertainties. SMC causes chattering, which can be reduced with specific techniques but is not fully eliminated in practice.	[49–57]
Active disturbance rejection control (ADRC) and Extended state observer (ESO)-based control	Estimates and compensates for disturbances in real time.	Performance depends strongly on observer tuning and bandwidth selection, is sensitive to measurement noise, and may struggle with fast-varying human dynamics.	[75,76]
Intelligence/Fuzzy, Neural and Reinforcement Learning Methods	Depending on the approach, these controllers can handle nonlinearities and uncertainties, learn user-specific torque patterns, adapt control gains, or optimise control policies through experience.	Requires training data, high computational load, uncertain real-time reliability in rehabilitation applications.	[17,58–63]
Hybrid Control (SMC+ Adaptive Fuzzy Logic, SMC+ Impedance, Fuzzy+ PID, Neural Network+ Bounded Nonlinear Control)	Combine the strengths of multiple controllers to improve robustness, accuracy, and adaptability compared with single-method approaches.	High complexity, risk of instability if not tuned, and challenging hardware implementation.	[77–81]

However, in real hardware implementations, SMC introduces a critical, still-unresolved issue known as chattering. Although many exoskeleton studies propose higher-order, adaptive, or intelligent SMC variants to reduce switching effects, recent evidence shows that chattering can persist in real-world systems. Liu Hsu et al. [82] showed that even advanced higher-order methods, such as the super-twisting algorithms, may still generate chattering when unmodeled dynamics or resonant modes are present, challenging the common assumption that modern SMC formulations are inherently chattering-free. These

observations are directly relevant to wearable exoskeletons, where sensor noise, actuator dynamics, mechanical compliance, and variability in human–robot interaction can affect practical controller performance. These limitations motivate a focused review of SMC-based control strategies with emphasis on tracking performance, chattering mitigation, sensing requirements, real-time implementation, and suitability for safe rehabilitation applications.

4. Sliding-Mode Control

Sliding-Mode Control is a nonlinear control technique recognised for its robustness against model uncertainties and external disturbances [83–85]. Unlike linear controllers, SMC uses discontinuous control laws to drive system trajectories to a predefined sliding surface, ensuring consistent performance despite uncertainties. Its simplicity and robustness have led to widespread use across domains such as electric drives [86,87], robotics [88,89], autonomous vehicles [90,91], spacecraft [92] and power electronics [93]. Even after many years of research, SMC remains an active area of study, with new work focusing on reducing chattering [94–96], utilising higher-order methods [97,98] and integrating it with smart systems, such as artificial intelligence [99–101].

Figure 2 shows that a typical SMC system operates in two phases. In the reaching phase, the system trajectory moves toward the sliding surface, where $S = 0$. In the sliding phase, once the trajectory is on the surface, it slides along it toward the origin, achieving asymptotic stability. This two-stage behaviour enables precise, stable control in the presence of disturbances and modelling errors, making SMC a foundational tool in robust nonlinear control theory [102].

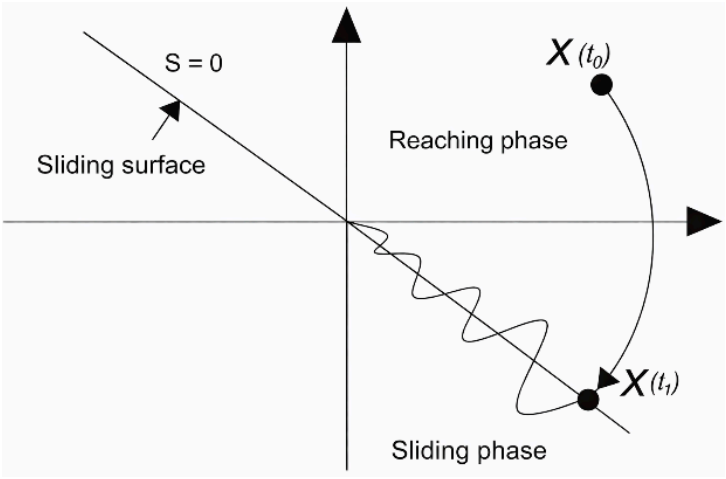


Figure 2. Graphical interpretation of SMC [103]. The curved trajectory and arrows indicate the system's movement towards the sliding surface during the reaching phase and its subsequent motion towards the origin during the sliding phase.

To better demonstrate the practical implementation of these principles, a block diagram of a typical SMC applied to a knee-exoskeleton system is presented in Figure 3. The block diagram represents the closed-loop interaction among sensing, control, actuation, and knee-joint dynamics. The desired joint angle is compared with the sensor-measured angle to compute the tracking error. This error and its derivative define the sliding surface, which represents the control objective. The SMC controller generates the control input u based on this sliding surface, typically using a discontinuous control law. This structure ensures robustness against uncertainties and disturbances. The actuator applies the control input, producing the torque needed to drive the knee joint toward the desired trajectory. The knee-joint dynamics respond to this torque while external disturbances affect them. Sensor

feedback continuously updates the system state, forming a closed-loop control that drives the sliding variable toward zero and achieves accurate, robust trajectory tracking.

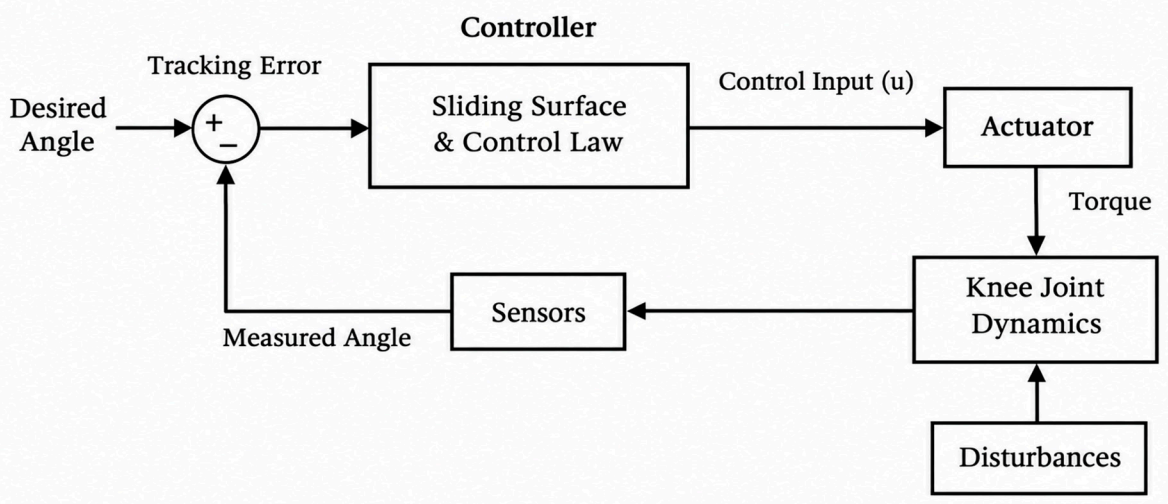


Figure 3. Block diagram of a typical SMC-based knee exoskeleton control system.

In a wearable knee exoskeleton, this feedback loop must operate continuously and in real time. Therefore, the controller's practical performance depends not only on the control law itself, but also on the quality of the measured signals, sensor noise, sampling and processing requirements, and the actuator's response. These implementation factors become particularly important when SMC is used in direct interaction with the user [96,104].

After establishing the theoretical foundation of SMC, the following section reviews the main SMC approaches proposed in the literature. This review systematically discusses classical and advanced SMC variants, focusing on their design principles, chattering-mitigation mechanisms, sensing and implementation requirements, and applications in knee and lower-limb exoskeleton systems with direct knee-related control or evaluation.

5. Overview of SMC in Knee and Lower-Limb Exoskeletons

Researchers have widely studied SMC for knee orthoses and lower-limb exoskeletons because it is robust to modelling uncertainties, external disturbances, and variations in human–robot interaction. The 126 studies included in this review show a gradual development from conventional first-order SMC toward terminal, higher-order, observer-based, adaptive, fractional-order, intelligent, and hybrid schemes. Most of these developments are motivated by two practical requirements: maintaining reliable tracking under uncertainty and reducing the chattering associated with discontinuous switching. In wearable systems, however, controller performance also depends strongly on the sensing system, actuator dynamics, real-time computation, and interaction with the user. The following discussion considers these aspects alongside the control structure.

5.1. Conventional, Integral, and Terminal SMC

Conventional SMC remains an important reference method in lower-limb exoskeleton control. Its relatively simple structure and robustness to matched uncertainties make it suitable for trajectory-tracking problems, and several studies have reported better tracking than conventional linear controllers under disturbances and parameter variations [105–107]. Conventional SMC has also been implemented on physical paediatric and rehabilitation exoskeleton platforms [108]. Its main limitation is discontinuous switching, which can cause chattering, increase control effort, and excite actuator or structural dynamics.

Integral and proxy-based SMC approaches have been introduced to address limitations associated with the reaching phase, tracking performance, and discontinuous control action. Integral SMC modifies the sliding manifold to reduce the reaching-phase effect and improve steady-state tracking. It has also been combined with neural-network estimation and feedforward compensation to deal with uncertain lower-limb dynamics [109]. Proxy-based SMC uses a virtual dynamic element between the controller and the physical joint, providing a smoother response while retaining the robustness of sliding-mode control. This principle has been demonstrated in knee-exoskeleton systems, such as BioKEX, where compliant and safer physical interaction was a central design consideration [110].

Terminal SMC represents a major branch of the literature. Unlike conventional SMC, terminal methods provide finite-time convergence. Researchers later developed non-singular formulations to avoid the singularity problem associated with some terminal manifolds. These approaches have been applied to powered knee orthoses and multi-joint lower-limb exoskeletons, with studies reporting improved convergence and robustness under disturbances and subject-dependent variations [111,112].

Fast and non-singular fast terminal SMC have also been investigated in paediatric gait systems, sit-to-stand assistance, and multi-DOF rehabilitation exoskeletons [113–118]. Some model-free designs use time-delay estimation to approximate uncertain dynamics instead of relying on a detailed exoskeleton model [119,120]. Others introduce dynamic boundary layers to reduce high-frequency switching around the sliding surface [121]. These developments improve convergence and tracking, but finite-time convergence alone does not eliminate chattering. Sensor noise, actuator bandwidth, mechanical compliance, and switching implementation remain important in practical systems.

5.2. Higher-Order, Super-Twisting, and Observer-Based SMC

Researchers have used higher-order SMC extensively to reduce the direct switching action applied to the actuator. Second-order methods have been investigated in knee orthoses, flexible exoskeletons, and fault-tolerant lower-limb systems [122–124]. In one knee-orthosis application, second-order SMC was combined with an RBF neural network and EMG information to estimate the intended knee movement and was evaluated experimentally with human participants [124].

The super-twisting algorithm is particularly common among higher-order approaches because it can provide a continuous control input while retaining finite-time convergence under appropriate conditions. It has been applied to pneumatic gait-training devices, lower-limb rehabilitation robots, impedance-controlled systems, and knee exoskeletons affected by uncertain disturbances [125–130]. Adaptive-gain versions have also been proposed to avoid selecting unnecessarily large, fixed gains when disturbance bounds are unknown [128]. Although these methods generally reduce switching effects relative to first-order SMC, their performance still depends on gain selection, signal quality, sampling, and actuator dynamics. It is therefore more appropriate to describe them as chattering-reduction methods rather than as universally chattering-free controllers.

Observer-based SMC forms another important group. Wearable exoskeletons contain several quantities that are difficult to measure directly, including user-generated torque, interaction disturbances, and sometimes joint velocity. Nonlinear disturbance observers, extended-state observers, sliding-mode observers, and uncertainty/disturbance estimators have therefore been combined with SMC to reconstruct these quantities and improve disturbance rejection [131–135].

Observer-assisted approaches can reduce the burden on the discontinuous switching term because they estimate part of the uncertainty explicitly. Similar concepts are used in ADRC–SMC and terminal-SMC architectures [48,136–138]. However, this benefit in-

troduces another practical trade-off. High observer bandwidth can improve disturbance estimation but may amplify encoder noise, quantisation effects, and unmodelled high-frequency dynamics. Observer tuning is therefore closely linked to sensing quality and hardware limitations.

5.3. Adaptive, Fractional-Order, and Intelligent SMC

Adaptive SMC is widely used where system parameters or human-related disturbances vary with time. Rather than selecting a fixed switching gain based on a conservative uncertainty bound, adaptive methods update controller gains according to the tracking error, sliding variable, or estimated uncertainty. Researchers have applied these approaches to rehabilitation, paediatric, hydraulic, and multi-joint lower-limb exoskeletons [111,116,139–144]. This can reduce unnecessary control effort, which is especially relevant in wearable devices where excessive torque or rapid switching may affect comfort. At the same time, adaptive laws introduce additional tuning parameters, and poorly selected adaptation rates can lead to excessive gains or oscillatory behaviour.

Fractional-order SMC provides greater flexibility in shaping the sliding dynamics by introducing a fractional derivative order. Fractional-order SMC have been combined with adaptive, terminal, non-singular fast terminal, and disturbance-observer structures [120,145–152]. Many of these studies report improved tracking or smoother control compared with integer-order methods. However, most evidence remains simulation based. Real-time implementation requires approximating the fractional operator, additional tuning, and more computational effort, and experimental evidence under realistic sensor noise and human interaction remains relatively limited.

Intelligent SMC is another prominent research direction. RBF neural networks have been used to approximate uncertain exoskeleton dynamics, human–robot interaction forces, and lumped disturbances [109,153–159]. ANFIS and fuzzy systems have similarly been integrated with SMC to adapt controller parameters or compensate for nonlinear behaviour [78,160–164]. These methods are attractive because obtaining an accurate analytical model of the combined human-exoskeleton system is often difficult.

Optimisation and learning methods have also been used to select parameters. Genetic algorithms, whale and grey-wolf optimisation, firefly methods, and improved sparrow-search strategies have been applied mainly to SMC gain tuning and multi-objective performance optimisation [150,165–168]. Reinforcement learning and recurrent neural networks have also appeared in more recent schemes [125,169,170]. These methods can improve selected performance indices and reduce manual tuning, but their results depend strongly on the training conditions or objective function. Better simulation performance does not necessarily demonstrate equivalent safety or robustness in a wearable system.

5.4. Hybrid SMC and Human–Robot Interaction-Oriented Control

Recent SMC research increasingly treats the exoskeleton as a human–robot system rather than a rigid mechanical plant. The user introduces variations in joint impedance, voluntary effort, interaction torque, body dimensions, and movement intention. For this reason, researchers often combine SMC with impedance, admittance, backstepping, compliant actuation, or intention-estimation methods.

Impedance- and admittance-based architectures are particularly useful because they explicitly regulate the relationship between motion and interaction force. Hybrid impedance–SMC has been studied on lower-limb exoskeletons, while adaptive and variable-admittance SMC has been proposed for rehabilitation and cooperative motion [79,171,172]. Paediatric and assist-as-needed systems have also combined finite-time SMC with variable admittance to adjust assistance according to user participation [173,174]. In these structures, the in-

ner controller usually provides robust trajectory tracking, while the outer interaction loop modifies the desired motion or assistance level.

Series elastic actuators offer another way of improving compliant physical interaction. Several studies combine SEA dynamics with robust, adaptive, or observer-based SMC [111,156,175,176]. Neural estimation and disturbance observers have also been used in SEA-based knee systems to compensate for uncertain human-exoskeleton dynamics [156]. These studies move the control objective beyond position tracking by considering interaction force and actuator compliance.

Human-intention sensing is also becoming more visible in the literature. EMG has been combined with sliding-mode control for intention recognition, event-triggered control, and activation of rehabilitation movements [113,124,177–179]. Other studies employ multiple sensing sources to estimate gait phase or user intention [180]. Such approaches are particularly relevant to wearable rehabilitation because the assistance should ideally respond to the user rather than impose a fixed trajectory independently of their contribution.

Backstepping–SMC and other hybrid architectures address the nonlinear coupled dynamics of multi-joint systems by combining SMC with recursive nonlinear control, ADRC, impedance/admittance regulation, central pattern generators, or fault-tolerant control [122,136,138,140,143,181–186]. These combinations can improve robustness and distribute different tasks across several control layers. Their main disadvantage is increased complexity, particularly when observers, adaptive laws, and learning algorithms are used simultaneously.

5.5. Practical Implementation, Validation, and Research Gaps

Despite substantial progress in controller design, validation varies considerably across the reviewed literature. Many studies rely on MATLAB/Simulink, ADAMS co-simulation, or other numerical environments [105,119,120,140,146,148]. These studies support controlled algorithm comparisons but cannot fully capture encoder noise, actuator bandwidth, backlash, communication delay, soft-tissue motion, joint misalignment, or unpredictable user behaviour.

A smaller but important group has progressed to physical prototypes and human-in-the-loop experiments. Examples include experimental knee orthoses, paediatric exoskeletons, SEA-based systems, and EMG- or assist-as-needed controllers [111–113,118,124,139,173,174,177,187]. However, many experimental studies involve few participants or short testing periods. Evidence from clinical populations is also less common than testing with healthy participants.

The sensing architecture is equally important for the practical implementation of SMC. Across the reviewed studies, feedback is obtained from joint encoders or potentiometers, force and interaction sensors, IMUs, actuator current or pressure measurements, SEA deformation, motion-capture systems, and surface EMG. Several studies implement control on real-time or embedded platforms rather than purely in simulation [108,109,156,180]. These examples show that SMC's practical behaviour depends on the full sensing–computation–actuation loop, not just the mathematical control law.

Chattering remains a recurring concern across all SMC families. Researchers have used boundary layers, saturation and hyperbolic-tangent functions, adaptive gains, super-twisting algorithms, disturbance observers, neural and fuzzy compensation, fractional-order surfaces, optimisation, and compliant actuation to reduce it. However, the evidence used to demonstrate chattering reduction is not consistent across studies. In many cases, conclusions rely on a visibly smoother control signal or lower tracking error rather than direct measurements of actuator vibration, interaction-force oscillation, or user discomfort. Therefore, a reduction in simulated switching should not automatically be interpreted as the elimination of chattering at the physical human-device interface.

Another limitation of this review is that it did not apply formal study-quality or risk-of-bias assessment; therefore, the evidence should be interpreted considering substantial heterogeneity in modelling assumptions, validation settings, and experimental designs.

Overall, the literature shows clear progress from relatively simple robust tracking controllers toward more integrated and user-oriented SMC architectures. Robustness and tracking performance are widely reported, but more sophisticated controllers often require more sensing, increase computational cost, and add tuning complexity. The main remaining gap is therefore not simply developing another SMC variant but demonstrating that the proposed methods remain effective under realistic sensor noise, actuator limitations, delays, changing user behaviour, and prolonged physical interaction. Future studies would benefit from more consistent reporting of sampling rates and actuator bandwidth, quantitative measures of chattering, larger human-subject evaluations, and clearer assessment of interaction forces, comfort, and safety.

To summarise these methodological differences, Table 2 compares the main SMC families identified in the reviewed literature in terms of their typical sliding structure, principal advantages, limitations, and representative references.

Table 2. Comparison of Sliding-Mode Control Methods.

SMC Method	Sliding Surface	Pros	Cons	References
Conventional (First Order) SMC	$S = \dot{e} + ce$, $c > 0$, where e is the tracking error in joint position(angle) or torque, depending on the control objective.	Robust to matching uncertainties; simple design; insensitive to parameter variations once on the sliding surface; the tracking error asymptotically converges to zero.	Chattering due to discontinuous control; reaching phase sensitive to uncertainties; high control effort; requires knowledge of uncertainty bounds and full-state feedback.	[105–108]
Higher-Order SMC/Super-Twisting SMC	$s = \dot{e} + ce$, $c > 0$ with higher order/super-twisting reaching law	Strong chattering reduction vs. 1st-order; better tracking of fast dynamics; finite-time convergence.	More complex design; needs higher-order error signals or observers; sensitive to noise and implementation challenges.	[122–130]
Fractional-Order SMC	$s = D^{\alpha}e + ce$, where D^{α} is the fractional derivative of order α $0 < \alpha < 1$, c > 0	Smoother control; faster reaching phase; reduced chattering; flexible dynamics modelling; improved tracking accuracy.	Needs fractional calculus tools/filters; higher implementation effort; more complex parameter tuning (α); complicated stability analysis; complexity and computational cost; hard to implement in a real-time system.	[120,145–152]
Terminal/Non-singular SMC	$s = \dot{e} + \beta\lvert e\rvert^{\frac{p}{q}} sgn(e)$, $\beta > 0$, $0 < \frac{p}{q} < 1$	Finite-time convergence; high tracking accuracy; robustness to matched uncertainties; potentially smoother control with appropriate design.	Conventional TSMC may suffer from singularity; exponent selection must satisfy design constraints; poor tuning may cause chattering; requires accurate position and velocity feedback.	[111–121]

Table 2. *Cont.*

SMC Method	Sliding Surface	Pros	Cons	References
Adaptive SMC	$s = \dot{e} + \lambda(t)e$, where $\lambda(t) > 0$ is a time-varying gain on the error term. With an adaptive gain law $\dot{k} = \gamma \lvert s \rvert, \gamma > 0$ is the adaptive rate.	Adapts to parameter variations and uncertainties; improves robustness under changing operating conditions with less dependence on precise model knowledge.	Adds complexity; requires adaptive-gain tuning; Convergence speed depends on γ; poor tuning may cause chattering or excessive knee torque; needs full state info; higher computational load.	[111,116,139–144]
Integral SMC	$s(t) = Ce(t) + D\dot{e}(t) + \int_0^t Fe(\tau)d\tau$, $C, D, F > 0$	Can eliminate the reaching phase when the sliding manifold is appropriately initialised to satisfy s (0) = 0; improves robustness to matched uncertainties and may reduce steady-state tracking error under suitable design conditions.	Chattering persists (still uses discontinuous sign function); computationally more complex; sensitive to measuring noise; higher control effort.	[109]
Observer-Based SMC	Conventional/terminal s + ESO/NDO/SMO/UDE	Better disturbance rejection; estimates unmeasured states or interaction torques	Observer tuning; noise amplification; extra computation	[131–138]
Hybrid/HRI-Oriented SMC	SMC combined with impedance, admittance, backstepping, SEA, ADRC, or intention estimation	Better human–robot interaction; compliant assistance; improved adaptability	High architecture and tuning complexity; harder real-time validation	[79,111,156,171–186]
Intelligent/optimised SMC	Basic s + NN/fuzzy/ANFIS/optimisation	Handles nonlinear uncertainty; online adaptation; reduced manual tuning	Higher computation; training/tuning burden; more complex stability analysis	[78,109,125,150,153–170]

As a result, despite substantial algorithmic sophistication, no consensus SMC framework guarantees provable chattering suppression at the human-joint interface while retaining robustness and finite-time performance that make SMC attractive for knee exoskeleton control. To further contextualise the quantitative comparisons presented in the following section, the validation approaches adopted in the reviewed studies are summarised in Figure 4.

Figure 4 shows that simulation-only validation remains the most common approach among the reviewed studies (46.03%). A further 34.13% combined simulation with experimental or hardware evaluation, while 19.84% relied primarily on experimental or hardware validation. Although much of the literature has moved beyond purely numerical evaluation, simulation remains dominant. This should be considered when comparing tracking and chattering performance, since practical factors such as sensor noise, actuator dynamics, communication delays, and human–robot interaction are not fully represented in numerical studies.

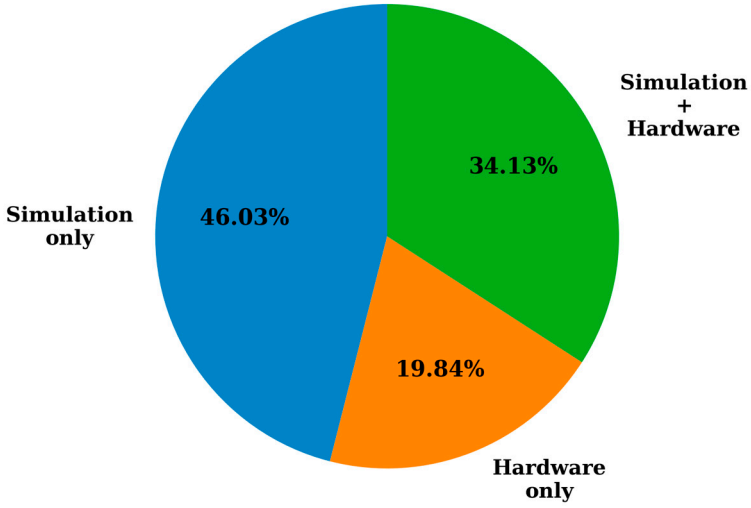


Figure 4. Distribution of validation approaches among the 126 studies included in the review.

To further examine the practical implementation of SMC-based exoskeleton control, Table 3 summarises representative studies with emphasis on sensing, real-time hardware, human interaction, and adaptive features.

Table 3. Representative implementation characteristics of SMC-based knee and lower-limb exoskeleton studies.

SMC Method	Sensors/Feedback	Validation/Real-Time Implementation	Human Interaction/Adaptation	References
Adaptive proxy-based SMC (APSMC)	Incremental knee encoder; EMG	Real-time powered knee orthosis experiments	2 healthy subjects; online gain adaptation; safety under abnormal tracking errors	[50]
Single-input adaptive fuzzy SMC (S-AFSMC)	Sole force/FRF sensing; six-axis HRI force sensing; joint feedback	Experimental lower-limb exoskeleton	Wearer intention estimated from gait phase and interaction force	[77]
RBFNN-based adaptive ISMC + feedforward control (PIDFF-ISMC)	Hip and knee encoders	Real-time experimental lower-limb exoskeleton using a Speedgoat platform.	Intelligent online uncertainty compensation; no clinical patient trial	[109]
Robust adaptive neural SMC (RASMC) + DOB	High-resolution knee encoder; SEA displacement sensor	Real-time hardware experiment (NI myRIO, 1 kHz)	Adaptive neural estimation of varying human/load dynamics; wearer assistance experiments	[156]
NDO-based robust terminal SMC	Knee encoder; muscular torque estimated by NDO	Real-time knee-orthosis experiment (dSPACE, 1 kHz)	3 healthy subjects; observer estimates wearer muscular torque	[135]

Table 3. *Cont.*

SMC Method	Sensors/Feedback	Validation/Real-Time Implementation	Human Interaction/Adaptation	References
Robust non-singular fast terminal SMC (RNFTSMC)	Myo Armband sEMG; joint-position feedback; motion capture for reference generation	Real-time mobile exoskeleton experiments.	Human intention activates sit-to-stand/stand-to-sit assistance; targeted at SCI and elderly users.	[113]
Second-order SMC (SoSMC) + RBFNN	Quadriceps EMG; joint-position feedback	dSPACE-based real-time knee-orthosis experiments	5 volunteers; EMG-driven intention estimation for knee flexion/extension	[124]
ESO-based nonlinear terminal SMC (ESO-F-NTSMC)	IMUs; joint encoders; plantar pressure sensors	Embedded-PC/CAN architecture; physical walking experiments.	3 human subjects during natural walking; active human-exoskeleton cooperation.	[188]

6. Comparison of Different SMC Methods

To quantitatively evaluate the effectiveness of SMC strategies in knee-joint exoskeleton, performance metrics including root mean square error (RMSE) and chattering, were considered. A detailed comparison of these metrics across the reviewed SMC-based studies is presented in Sections 6.1 and 6.2, respectively.

6.1. RMSE Comparison of SMC-Based Methods

RMSE is one of the most widely used performance metrics for evaluating the trajectory-tracking accuracy of knee exoskeleton controllers. It measures the average deviation between the desired and actual joint angles over time. It provides an overall indication of tracking precision and closed-loop stability during gait or rehabilitation movements. For a knee-joint angle control system, RMSE is typically defined as

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\theta_d(i) - \theta(i))^2}$$

where $\theta d(i)$ is the desired knee-joint angle at time step i, $\theta(i)$ is the measured (actual) knee-joint angle at time step i and N is the total number of sampled time points. Although RMSE is widely used in trajectory-tracking studies, it was not reported numerically in all the reviewed publications. A systematic audit of the 126 included studies identified those reporting explicit numerical RMSE values for knee-joint tracking. To improve traceability and avoid uncertainty associated with extracting values from graphical plots, only directly reported numerical knee-tracking RMSE values were used in the quantitative comparison presented in Figure 5.

Among the 126 included studies, 32 explicitly reported numerical RMSE values for knee-joint trajectory tracking. Of these, 25 were initially identified as candidates for within-study comparisons. After a detailed assessment of the reported numerical values, comparator selection, and test scenarios, we excluded five comparisons because they did not meet the criteria for an unambiguous, reproducible paired comparison. Consequently, 20 studies were retained for the quantitative synthesis presented in Figure 5. Knee-joint RMSE was selected as the common outcome because the review focuses specifically on knee-related control performance; RMSE values reported only for the hip, ankle, or other outcomes were excluded.

An engineering-focused appraisal was undertaken to contextualise the 20 within-study comparisons presented in Figure 5. The appraisal considered validation settings, comparator tuning, disturbance and parameter-uncertainty testing, sensing arrangements, sampling rates, and human-subject involvement. Available source evidence and reporting limitations are documented in Supplementary Table S1. The appraisal identified differences in experimental conditions, controller architectures, and reporting completeness across studies. Accordingly, the reported RMSE reductions are interpreted as descriptive within-study findings rather than directly comparable estimates of controller effectiveness. Where we could not establish equivalent comparator tuning or independent experimental evidence, we explicitly acknowledged these limitations.

For each study, one within-study knee-joint RMSE comparison was selected using documented selection criteria. Priority was given to the primary comparison explicitly reported by the authors, preferably against the closest conventional or component-matched controller. The proposed method and comparator were required to be evaluated for the same knee-joint tracking task and under matched test conditions. When several test scenarios were available, an explicitly identified primary or otherwise unambiguous scenario was selected. Comparisons requiring arbitrary selection among participants, gait phases, or knee sides, or those involving ambiguous numerical values or outcome definitions, were excluded. No arithmetic averaging of RMSE values across separate participants, joints, or gait phases was performed. Comparator selection was not based on maximising the reported percentage improvement. The selection rationale and original numerical values are documented in Supplementary Table S1.

Direct comparison of absolute RMSE values across different publications remains inappropriate because the studies use different exoskeleton models, reference trajectories, disturbance conditions, controller parameters, sampling procedures, and evaluation windows. Therefore, the present analysis focuses on within-study relative performance, where the proposed SMC-based method is compared with the corresponding comparator evaluated under the same study-specific conditions.

For each eligible comparison, the percentage reduction in knee-joint RMSE was calculated relative to the comparator as

$$\text{RMSE improvement}(\%) = \frac{\text{RMSE}_{\text{comparator}} - \text{RMSE}_{\text{proposed}}}{\text{RMSE}_{\text{comparator}}} \times 100.$$

This normalisation enables the relative improvement achieved by different SMC-based controllers to be visualised without treating absolute RMSE values from heterogeneous studies as directly comparable. The underlying RMSE values, controller pairs, units, and study conditions are provided in the Supplementary Table S1.

Figure 5 summarises the within-study percentage reductions in knee-joint tracking RMSE reported for the included SMC-based control strategies. The corresponding studies and comparator-based evaluations are documented in References [189–198], with further methodological details and numerical results provided in Supplementary Table S1.

Figure 6 further examines disturbance robustness using only studies that explicitly reported numerical knee-joint RMSE values for the same controller under matched undisturbed and disturbed conditions.

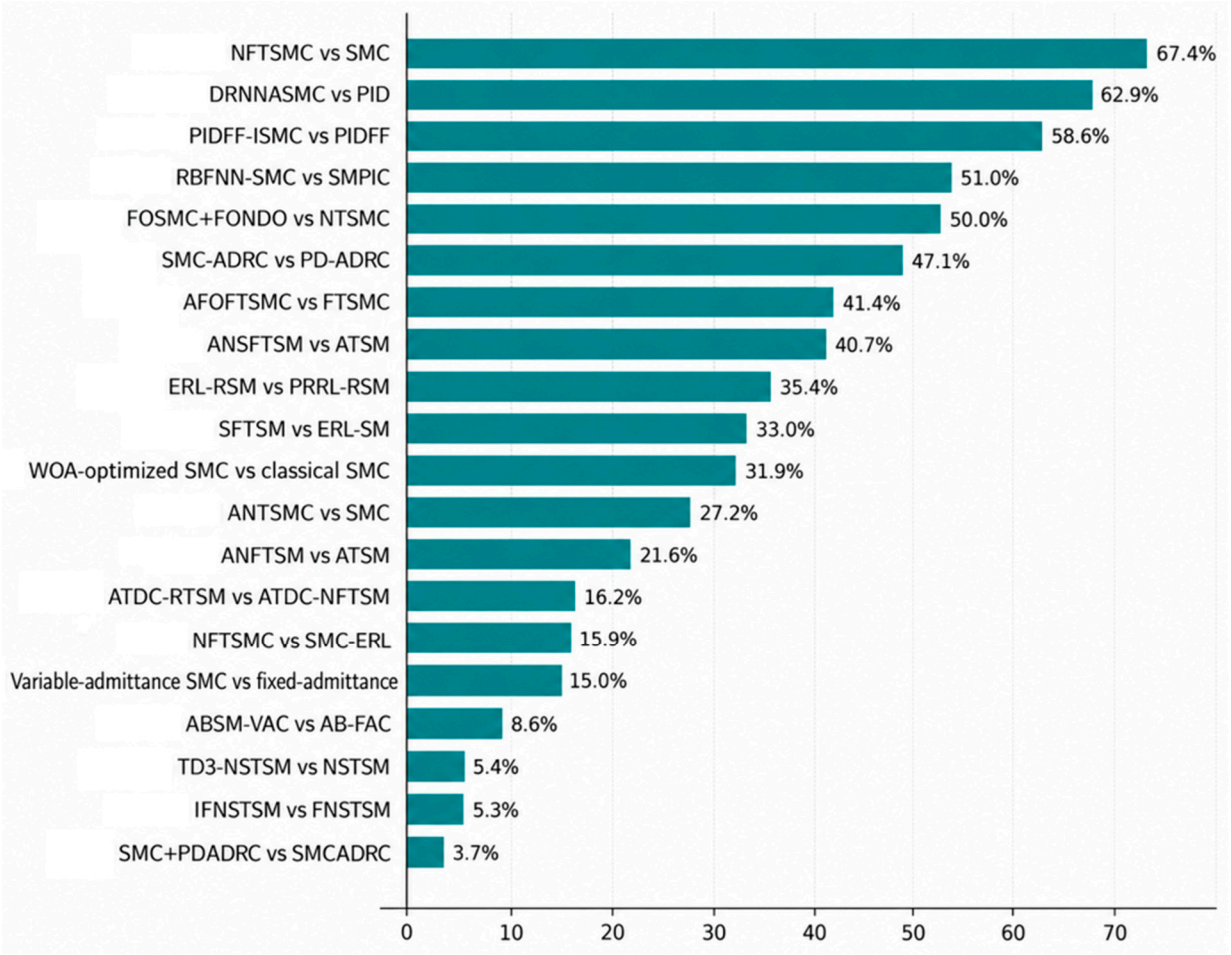


Figure 5. Within-study percentage reduction in knee-joint RMSE achieved by the proposed SMC-based controllers relative to the corresponding comparator reported in each study. The references corresponding to the bars are [48,109,111,114–117,136,139,147,149,153,165,169,173,174,187,189,192,198]. Only studies providing explicit numerical knee-tracking RMSE values were included. Positive values indicate lower RMSE with the proposed method.

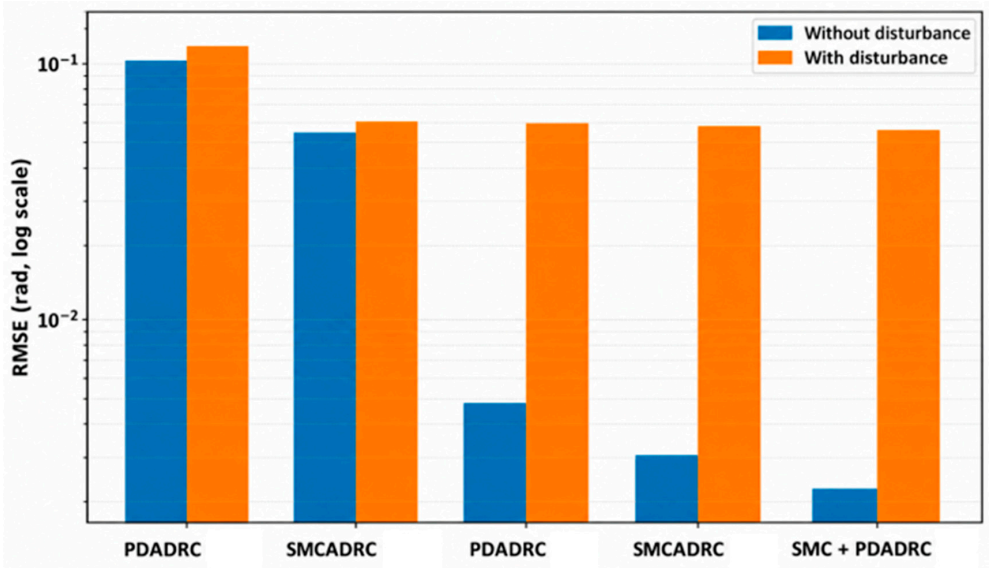


Figure 6. Knee-joint RMSE under matched undisturbed and disturbed conditions for selected controllers reporting explicit numerical values in both cases [48,136].

The numerical knee-joint RMSE values used in Figure 6 are summarised in Table 4. Only studies reporting explicit numerical RMSE values for the same controller under matched undisturbed and disturbed conditions were included.

Table 4. Knee-joint RMSE values under matched undisturbed and disturbed conditions used in Figure 6.

SMC Method	RMSE Without Disturbance (Rad)	RMSE with Disturbance (Rad)	Disturbance Condition	References
Proportional–Derivative Active Disturbance Rejection Control (PDADRC)	0.1022	0.1141	Load disturbance applied to the knee joint	[136]
Sliding-Mode-Control-Based Active Disturbance Rejection Control (SMCADRC)	0.0541	0.0591	Load disturbance applied to the knee joint	[136]
PDADRC	0.0038	0.0584	Constant load disturbance, 0.5 N·m	[48]
SMCADRC	0.0023	0.0568	Constant load disturbance, 0.5 N·m	[48]
SMC + PDADRC	0.0017	0.0547	Constant load disturbance, 0.5 N·m	[48]

As shown in Table 4, the presence of external disturbance increased knee-joint RMSE for all reported controllers, although the magnitude of degradation differs across the matched cases. In both studies, the ADRC-based controllers exhibit higher RMSE under disturbed conditions than under the corresponding undisturbed conditions. The increase is relatively small for the controllers reported in [136], whereas a substantially larger increase is observed under the 0.5 Nm constant load disturbance reported in [48]. These results illustrate that the effect of disturbance on tracking accuracy depends on the controller and the disturbance conditions considered within each study.

However, only two studies reported explicit numerical knee-joint RMSE values for the same controller under both undisturbed and disturbed conditions. Therefore, interpret Figure 6 as a within-study illustration of disturbance sensitivity rather than a general ranking of robustness across all reviewed SMC methods.

6.2. Chattering Mitigation Across the Reviewed Studies

To systematically analyse how chattering is addressed in SMC-based knee and lower-limb exoskeleton studies, the literature was categorised according to the primary mechanism used to mitigate chattering. Rather than enforcing a predefined control taxonomy, the classification focuses on the dominant physical or algorithmic strategy used to reduce high-frequency oscillations, such as smoothing the switching term, higher-order sliding modes, observer-based compensation, or structural isolation of discontinuities. Table 5 summarises the main chattering-mitigation mechanisms identified across the reviewed studies and provides representative references for each category. For example, Gao et al. [189] developed a dual RBF neural-network adaptive sliding-mode controller to compensate for friction and external disturbances in a lower-limb rehabilitation exoskeleton. This approach illustrates the integration of neural-network estimation with SMC, although its primary reported objective was improved tracking and disturbance compensation rather than the quantitative assessment of chattering reduction.

Table 5. Strategies for chattering reduction in SMC-based controllers and key references.

Strategy Type	Description	n	Percentage	References
Boundary-Layer/Smooth Switching	Replacing discontinuous sign(s) with continuous approximations (saturation, tanh, exponential or discrete boundary layers) to smooth control action and suppress chattering.	20	43.5%	[96,109,111,112,114, 121,132,144,151,152, 156,158,166,169,173, 177,190–193]
Proxy-Based Structural Isolation	Applying the discontinuous sliding action to a virtual proxy system while the physical joint is driven by smooth proxy–joint dynamics, avoiding direct switching at the human-joint interface.	3	6.5%	[110,194,195]
Neural/Fuzzy Integration	Replacing or reshaping the switching term using neural networks or fuzzy inference systems to generate continuous control inputs and suppress chattering.	2	4.3%	[154,162]
Observer-Based Compensation	Employing disturbance or extended-state observers to estimate and cancel uncertainties, reducing the required switching gain and indirectly mitigating chattering.	4	8.7%	[136,138,147,196]
Higher-Order/Terminal SMC	Using higher order, terminal or fast terminal sliding surfaces to achieve finite-time convergence with smoother control action compared to classical SMC.	10	21.7%	[113,117,118,123,125, 142,150,179,187,197]
Other/Novel Mitigation	Other explicitly attributed approaches, including switching-term restructuring or parameter tuning.	7	15.2%	[48,139,149,160,172, 183,198]

A total of 46 unique studies were classified according to their primary reported chattering-mitigation mechanism, while the remaining 80 studies could not be reliably assigned to these categories based on the available evidence. To avoid double counting, each classified study was assigned to only one primary category based on the dominant mitigation mechanism supported by the source evidence. The classification criteria, study-level decisions, and supporting evidence are documented in Supplementary Table S4.

Figure 7 summarises the distribution of the 46 classified studies across the six primary chattering-mitigation categories.

Sun et al. [198] proposed an adaptive time-delay control strategy incorporating recursive terminal sliding-mode control for lower-limb exoskeleton gait tracking. Their study shows how terminal sliding-mode formulations can integrate adaptive compensation to improve tracking performance and disturbance robustness. However, improved tracking performance should not automatically be interpreted as evidence of reduced chattering.

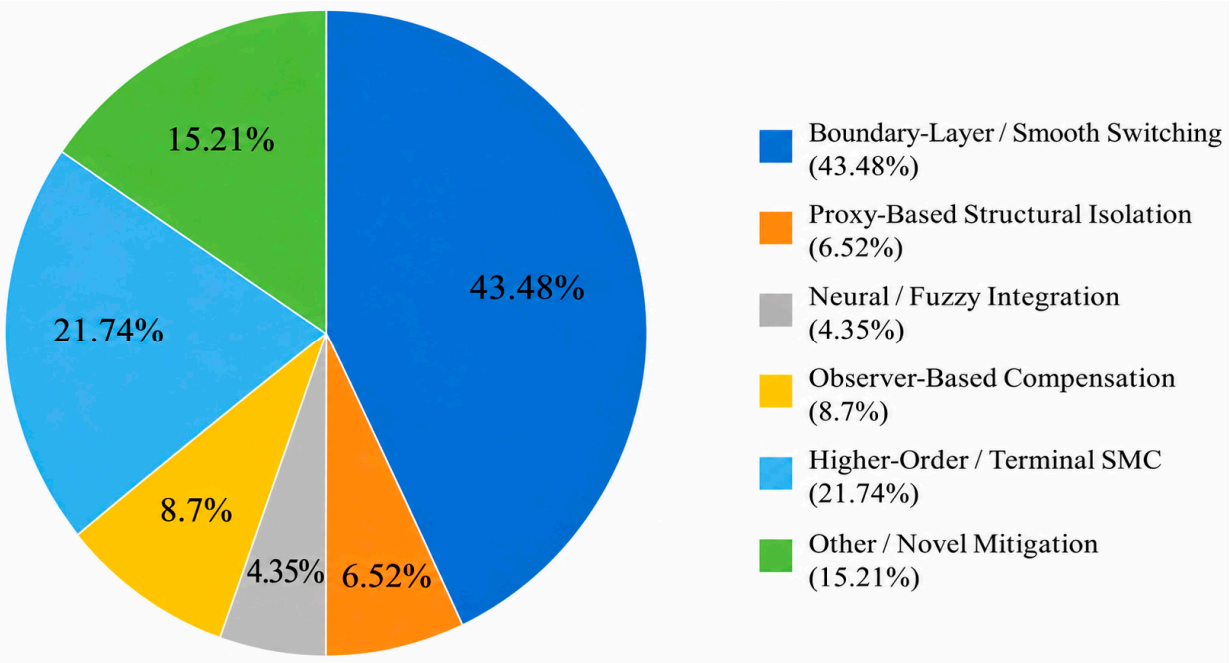


Figure 7. Distribution of chattering-mitigation strategies across the 46 classified SMC-based knee and lower-limb exoskeleton studies.

Within the classified subset, boundary-layer and smooth-switching techniques constituted the largest identified chattering-mitigation category (43.5%), followed by higher-order or terminal SMC (21.7%), other or novel mitigation approaches (15.2%), and observer-based compensation (8.7%). Proxy-based structural isolation accounted for 6.5%, while neural/fuzzy integration represented 4.3% of the classified studies. These proportions represent the distribution of the primary chattering-mitigation mechanisms assigned to the 46 classified studies. They should not be interpreted as measures of comparative effectiveness or as evidence of the prevalence of these strategies across all 126 included studies.

Importantly, adopting a chattering-mitigation mechanism does not necessarily eliminate residual chattering. Narayan et al. [192] compared four reaching laws within a robust sliding-mode control framework for a paediatric lower-limb exoskeleton. They employed a continuous hyperbolic tangent approximation of the discontinuous switching function and evaluated chattering using a quantitative chattering indicator. Their findings showed that the reaching law providing the lowest tracking RMSE did not necessarily yield the lowest chattering level, highlighting the need to assess tracking accuracy and switching-induced oscillations separately.

In many of the reviewed studies, chattering reduction was inferred qualitatively from smoother control-input, torque, or sliding-variable responses rather than evaluated using a standardised quantitative metric. Consequently, direct numerical comparison of chattering performance across studies is not currently reliable because the reported evaluation variables, scales, operating conditions, and validation platforms differ substantially.

For completeness and traceability, the additional studies included in the systematic review, which are documented in Supplementary Table S3 but not individually discussed in the preceding sections, are cited here [199–226]. These studies form part of the original set of 126 included studies and provide further supporting evidence for the review.

7. Conclusions

This review analysed Sliding-Mode Control strategies applied to knee and lower-limb exoskeletons with direct knee-related control or evaluation, with particular attention to

tracking accuracy and chattering behaviour. The surveyed studies generally show that SMC provides robust tracking under nonlinear dynamics, disturbances, and uncertainties inherent in human–robot interaction. Within individual studies, advanced SMC variants generally report lower RMSE compared to conventional SMC when evaluated under identical conditions. However, direct comparison of RMSE values across different publications remains limited due to variations in system models, gait tasks, reference trajectories, disturbance assumptions, and evaluation protocols. As a result, reported RMSE values are more informative in terms of relative improvement trends than as absolute performance indicators.

Despite substantial algorithmic developments, chattering remains a persistent practical challenge. Within the subset of studies for which a primary chattering-mitigation mechanism could be identified, boundary-layer and smooth-switching approaches constituted the largest category. However, this distribution should not be interpreted as evidence that smoothing is generally preferred over structural controller redesign across the entire literature, as the remaining studies could not be classified under the adopted criteria. Although such strategies reduce visible oscillations, residual high-frequency effects often remain due to unmodelled dynamics, actuator limitations, discretisation, and measurement noise. Higher-order methods, including super-twisting algorithms, offer theoretical advantages but do not fully eliminate chattering in realistic hardware implementations, especially when compliance and sampling effects are considered. Observer-based and intelligent SMC approaches further mitigate oscillations by reducing switching gains through disturbance estimation or function approximation; however, these methods introduce additional trade-offs related to noise sensitivity, bandwidth tuning, and implementation complexity.

Importantly, smoother control inputs do not automatically ensure safe and comfortable interaction at the human-joint interface. The absence of standardised chattering metrics and the fact that simulation remains the most common validation approach, further limit the ability to assess high-frequency interaction effects.

Overall, while SMC-based controllers demonstrate strong robustness and tracking capability in knee and lower-limb exoskeleton applications, a unified framework that guarantees chattering suppression under realistic human-interactive conditions has not yet been established. Future research should prioritise structurally grounded and constraint-aware control design, supported by standardised evaluation metrics and rigorous hardware validation. Addressing chattering in a systematic and experimentally verified manner remains essential for translating the theoretical robustness of SMC into safe, reliable, and human-compatible knee and lower-limb exoskeleton systems.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/electronics15215160/s1. Table S1: Paired knee-joint RMSE values, comparator and scenario selection, exclusion reasons, and engineering-focused appraisal of the studies included in Figure 5. Table S2: Database-specific search strategies, Boolean search strings, search fields, filters, and search dates. Table S3: Report-to-study register, bibliographic information, source provenance, companion-publication mapping, and PRISMA screening summary. Table S4: Study-level classification of chattering-mitigation mechanisms, category-assignment criteria, supporting evidence, and reasons for unclassified studies.

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References

1. Masengo, G.; Zhang, X.; Dong, R.; Alhassan, A.B.; Hamza, K.; Mudaheranwa, E. Lower limb exoskeleton robot and its cooperative control: A review, trends, and challenges for future research. *Front. Neurorobot.* **2023**, *16*, 913748. [CrossRef] [PubMed]
2. Chen, B.; Zhong, C.-H.; Zhao, X.; Ma, H.; Guan, X.; Li, X.; Liang, F.-Y.; Cheng, J.C.Y.; Qin, L.; Law, S.-W. A wearable exoskeleton suit for motion assistance to paralysed patients. *J. Orthop. Transl.* **2017**, *11*, 7–18. [CrossRef] [PubMed]
3. Shi, D.; Zhang, W.; Zhang, W.; Ding, X. A review on lower limb rehabilitation exoskeleton robots. *Chin. J. Mech. Eng.* **2019**, *32*, 74. [CrossRef]
4. Pons, J.L. *Wearable Robots: Biomechatronic Exoskeletons*; John Wiley & Sons: Hoboken, NJ, USA, 2008.
5. Yao, Y.; Shao, D.; Tarabini, M.; Moezi, S.A.; Li, K.; Saccomandi, P. Advancements in Sensor Technologies and Control Strategies for Lower-Limb Rehabilitation Exoskeletons: A Comprehensive Review. *Micromachines* **2024**, *15*, 489. [CrossRef] [PubMed]
6. Sun, Y.; Tang, Y.; Zheng, J.; Dong, D.; Chen, X.; Bai, L. From sensing to control of lower limb exoskeleton: A systematic review. *Annu. Rev. Control* **2022**, *53*, 83–96. [CrossRef]
7. Wilmart, R.; Garone, E.; Innocenti, B. The use of robotics devices in knee rehabilitation; a critical review. *Muscles Ligaments Tendons J.* **2019**, *9*, 21–48. [CrossRef]
8. Tang, X.; Wang, X.; Xue, Y.; Yin, R.; Yang, J. A study of knee exoskeleton configuration based on lower limb motion characteristics analysis. *Machines* **2023**, *11*, 709. [CrossRef]
9. Gunnell, A.J.; Sarkisian, S.V.; Hayes, H.A.; Foreman, K.B.; Gabert, L.; Lenzi, T. Powered knee exoskeleton improves sit-to-stand transitions in stroke patients using electromyographic control. *Commun. Eng.* **2025**, *4*, 104. [CrossRef] [PubMed]
10. Zhang, L.; Liu, G.; Han, B.; Wang, Z.; Li, H.; Jiao, Y. Assistive devices of human knee joint: A review. *Robot. Auton. Syst.* **2020**, *125*, 103394. [CrossRef]
11. Boling, M.C.; Padua, D.A.; Prentice, W.E. Rehabilitation of Knee Injuries. In *Rehabilitation Techniques for Sports Medicine and Athletic Training*; Routledge: London, UK, 2024; pp. 627–696.
12. Divekar, N.V.; Thomas, G.C.; Yerva, A.R.; Frame, H.B.; Gregg, R.D. A versatile knee exoskeleton mitigates quadriceps fatigue in lifting, lowering, and carrying tasks. *Sci. Robot.* **2024**, *9*, eadr8282. [CrossRef] [PubMed]
13. Xu, Q.; Li, J.; Jiang, N.; Yuan, X.; Liu, S.; Yang, D.; Ren, X.; Wang, X.; Yang, M.; Liu, Y. A Study on the Design of Knee Exoskeleton Rehabilitation Based on the RFPBS Model. *Biomimetics* **2024**, *9*, 410. [CrossRef] [PubMed]
14. Lysholm, J.; Nordin, M.; Ekstrand, J.; Gillquist, J. The effect of a patella brace on performance in a knee extension strength test in patients with patellar pain. *Am. J. Sports Med.* **1984**, *12*, 110–112. [CrossRef] [PubMed]
15. Mashud, G.; Hasan, S.; Alam, N. Advances in Control Techniques for Rehabilitation Exoskeleton Robots: A Systematic Review. *Actuators* **2025**, *14*, 108. [CrossRef]
16. Neťuková, S.; Bejtic, M.; Malá, C.; Horáková, L.; Kutílek, P.; Kauler, J.; Krupička, R. Lower limb exoskeleton sensors: State-of-the-art. *Sensors* **2022**, *22*, 9091. [CrossRef] [PubMed]
17. Almaghout, K.; Tarvirdizadeh, B.; Alipour, K.; Hadi, A. RBF neural network-based admittance PD control for knee rehabilitation robot. *Robotica* **2022**, *40*, 4512–4534. [CrossRef]
18. Abbass, A.M.; Saleh, B.J.; Mezher, L.S. Design of optimized desired optimal controller (doc)-based multivariable model reference adaptive control (mrac) algorithm for robotic human knee flexion during gait. *Rev. Intell. Artif.* **2024**, *38*, 541. [CrossRef]
19. Amiri, M.S.; Ramli, R.; Ibrahim, M.F. Initialized model reference adaptive control for lower limb exoskeleton. *IEEE Access* **2019**, *7*, 167210–167220. [CrossRef]
20. Yang, M.; Wang, X.; Zhu, Z.; Xi, R.; Wu, Q. Development and control of a robotic lower limb exoskeleton for paraplegic patients. *Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci.* **2019**, *233*, 1087–1098. [CrossRef]
21. Dos Santos, W.M.; Caurin, G.A.; Siqueira, A.A. Design and control of an active knee orthosis driven by a rotary series elastic actuator. *Control Eng. Pract.* **2017**, *58*, 307–318. [CrossRef]
22. Wehbi, F.e.Z.; Huo, W.; Amirat, Y.; El Rafei, M.; Khalil, M.; Mohammed, S. Active impedance control of a knee-joint orthosis during swing phase. In *Proceedings of the 2017 International Conference on Rehabilitation Robotics (ICORR)*; IEEE: Piscataway, NJ, USA, 2017; pp. 435–440.
23. Shepherd, M.K.; Rouse, E.J. Design and validation of a torque-controllable knee exoskeleton for sit-to-stand assistance. *IEEE/ASME Trans. Mechatron.* **2017**, *22*, 1695–1704. [CrossRef]
24. Xia, Y.; Wei, W.; Lin, X.; Li, J. Optimization of Torque-Control Model for Quasi-Direct-Drive Knee Exoskeleton Robots Based on Regression Forecasting. *Sensors* **2024**, *24*, 1505. [CrossRef] [PubMed]

25. Huang, T.-H.; Zhang, S.; Yu, S.; MacLean, M.K.; Zhu, J.; Di Lallo, A.; Jiao, C.; Bulea, T.C.; Zheng, M.; Su, H. Modeling and stiffness-based continuous torque control of lightweight quasi-direct-drive knee exoskeletons for versatile walking assistance. *IEEE Trans. Robot.* **2022**, *38*, 1442–1459. [CrossRef] [PubMed]
26. Liu, X.; Zhou, Z.; Mai, J.; Wang, Q. Real-time mode recognition based assistive torque control of bionic knee exoskeleton for sit-to-stand and stand-to-sit transitions. *Robot. Auton. Syst.* **2019**, *119*, 209–220. [CrossRef]
27. Huo, W.; Mohammed, S.; Amirat, Y. Impedance reduction control of a knee joint human-exoskeleton system. *IEEE Trans. Control Syst. Technol.* **2018**, *27*, 2541–2556. [CrossRef]
28. Martínez, A.; Durrough, C.; Goldfarb, M. A single-joint implementation of flow control: Knee joint walking assistance for individuals with mobility impairment. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2020**, *28*, 934–942. [CrossRef] [PubMed]
29. Saidi, I.; Hammami, A. Sliding mode control of an actuated knee joint orthosis. *Curr. Signal Transduct. Ther.* **2021**, *16*, 262–268. [CrossRef]
30. Utkin, V.; Hoon, L. Chattering Problem in Sliding Mode Control Systems. In *Proceedings of the International Workshop on Variable Structure Systems, 2006. VSS'06*; IEEE: Piscataway, NJ, USA, 2006; pp. 346–350.
31. Shtessel, Y.; Edwards, C.; Fridman, L.; Levant, A. *Sliding Mode Control and Observation*; Springer: Berlin/Heidelberg, Germany, 2014; Volume 10.
32. Baik, I.-C.; Kim, K.-H.; Youn, M.-J. Robust nonlinear speed control of PM synchronous motor using boundary layer integral sliding mode control technique. *IEEE Trans. Control Syst. Technol.* **2000**, *8*, 47–54. [CrossRef]
33. Sun, G.; Wu, C.; Li, X.; Ma, Z.; Xu, S.; Shao, X. *Fractional-Order Sliding Mode Control: Methodologies and Applications*; Springer: Berlin/Heidelberg, Germany, 2024.
34. Yu, X.; Feng, Y.; Man, Z. Terminal sliding mode control—An overview. *IEEE Open J. Ind. Electron. Soc.* **2020**, *2*, 36–52. [CrossRef]
35. Hamayun, M.T.; Edwards, C.; Alwi, H.; Hamayun, M.T.; Edwards, C.; Alwi, H. *Integral Sliding Mode Control*; Springer: Berlin/Heidelberg, Germany, 2016.
36. Taheri, B.; Case, D.; Richer, E. Force and stiffness backstepping-sliding mode controller for pneumatic cylinders. *IEEE/ASME Trans. Mechatron.* **2014**, *19*, 1799–1809. [CrossRef]
37. Azar, A.T.; Zhu, Q. *Advances and Applications in Sliding Mode Control Systems*; Springer: Berlin/Heidelberg, Germany, 2015.
38. Utkin, V.; Poznyak, A.; Orlov, Y.V.; Polyakov, A. *Road Map for Sliding Mode Control Design*; Springer: Berlin/Heidelberg, Germany, 2020.
39. Pratt, J.E.; Krupp, B.T.; Morse, C.J.; Collins, S.H. The RoboKnee: An exoskeleton for enhancing strength and endurance during walking. In *Proceedings of the IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA'04. 2004*; IEEE: Piscataway, NJ, USA, 2004; pp. 2430–2435.
40. Liang, G.; Ye, W.; Xie, Q. PID control for the robotic exoskeleton: Application to lower extremity rehabilitation. In *Proceedings of the 2012 IEEE International Conference on Mechatronics and Automation*; IEEE: Piscataway, NJ, USA, 2012; pp. 2345–2350.
41. Wan Salleh, W.M.S. Development of Knee Joint Angle Trajectory Tracking for Leg Support Mechanism. Doctoral Dissertation, Universiti Tun Hussein Onn Malaysia, Johor Darul Ta'zim, Malaysia, 2015.
42. Munadi, M.; Nasir, M.; Ariyanto, M.; Iskandar, N.; Setiawan, J. Design and simulation of PID controller for lower limb exoskeleton robot. In *Proceedings of the AIP Conference Proceedings*; AIP Publishing LLC: Melville, NY, USA, 2018.
43. Karmani, N.; Saidi, I.; Mbarek, H. PID Control of a Lower Limb Rehabilitation Exoskeleton. *Prz. Elektrotech.* **2024**, *2024*, 292–295. [CrossRef]
44. Dai, X.; Zhou, Z.; Wang, Z.; Rong, X.; Wang, Q. Admittance Control Based Gait Intervention Strategy of Knee Exoskeleton for Stance Phase Support. In *Proceedings of the 2024 IEEE International Conference on Advanced Intelligent Mechatronics (AIM)*; IEEE: Piscataway, NJ, USA, 2024; pp. 327–332.
45. Chen, B.; Zhou, L.; Zi, B.; Li, E.; Zhang, D. Adaptive Admittance Control Strategy for a Robotic Knee Exoskeleton With a Nonlinear Variable Stiffness Actuator. *IEEE/ASME Trans. Mechatron.* **2024**, *30*, 1888–1899. [CrossRef]
46. Peng, F.; Wen, H.; Zhang, C.; Xu, B.; Li, J.; Su, H. Adaptive robust force position control for flexible active prosthetic knee using gait trajectory. *Appl. Sci.* **2020**, *10*, 2755. [CrossRef]
47. Rifai, H.; Mohammed, S.; Daachi, B.; Amirat, Y. Adaptive control of a human-driven knee joint orthosis. In *Proceedings of the 2012 IEEE International Conference on Robotics and Automation*; IEEE: Piscataway, NJ, USA, 2012; pp. 2486–2491.
48. Alawad, N.A.; Humaidi, A.J.; Alaraji, A.S. A novel approach of multi-loop control based-ADRC for improving lower knee position exoskeleton system. *Int. Rev. Appl. Sci. Eng.* **2023**, *14*, 316–324. [CrossRef]
49. Mefoued, S.; Mohammed, S.; Amirat, Y. Toward movement restoration of knee joint using robust control of powered orthosis. *IEEE Trans. Control Syst. Technol.* **2013**, *21*, 2156–2168. [CrossRef]
50. Ding, G.; Huo, W.; Huang, J.; Amirat, Y.; Mohammed, S. Robust and Safe Control of a Knee Joint Orthosis. In *Proceedings of the 2018 IEEE International Conference on Intelligence and Safety for Robotics (ISR)*; IEEE: Piscataway, NJ, USA, 2018; pp. 343–348.
51. Aljuboury, A.S.; Hameed, A.H.; Ajel, A.R.; Humaidi, A.J.; Alkhayyat, A.; Mhdawi, A.K.A. Robust adaptive control of knee exoskeleton-assistant system based on nonlinear disturbance observer. *Actuators* **2022**, *11*, 78. [CrossRef]

52. Rigatos, G.G. Nonlinear optimal control for robotic exoskeletons with electropneumatic actuators. *Robot. Intell. Autom.* **2024**, *44*, 411–446. [CrossRef]
53. Rigatos, G.; Abbaszadeh, M.; Pomares, J.; Wira, P. A nonlinear optimal control approach for a lower-limb robotic exoskeleton. *Int. J. Humanoid Robot.* **2020**, *17*, 2050018. [CrossRef]
54. Yadav, P.S.; Singh, N. Robust control of two link rigid manipulator. *Int. J. Inf. Electron. Eng.* **2015**, *5*, 3–8. [CrossRef]
55. Gupta Roy, R.; Ghoshal, D. Adaptive second-order sliding-mode controller for shank-foot orthosis system. *Int. J. Control* **2019**, *92*, 1580–1589. [CrossRef]
56. Ajayi, M.O.; Djouani, K.; Hamam, Y. Bounded Control of an Actuated Lower-Limb Exoskeleton. *J. Robot.* **2017**, *2017*, 2423643. [CrossRef]
57. Al-Dujailii, A.Q.; Hasan, A.F.; Humaidi, A.J.; Al-Jodah, A. Anti-disturbance control design of Exoskeleton Knee robotic system for rehabilitative care. *Heliyon* **2024**, *10*, e28911. [CrossRef] [PubMed]
58. Sharma, R.; Gaur, P.; Bhatt, S.; Joshi, D. Optimal fuzzy logic-based control strategy for lower limb rehabilitation exoskeleton. *Appl. Soft Comput.* **2021**, *105*, 107226. [CrossRef]
59. Sayyaadi, H.; Zareh, S.H. Intelligent control of an MR prosthesis knee using of a hybrid self-organizing fuzzy controller and multidimensional wavelet NN. *J. Mech. Sci. Technol.* **2017**, *31*, 3509–3518. [CrossRef]
60. Arof, S.; Noorsal, E.; Yahaya, S.; Hussain, Z.; Safie, M.; Ali, Y.; Abdullah, M.; Setumin, S. Improvised Fuzzy Logic Controller Using Feedforward, Feedback Offset, And Proportional Integral For Knee Extension Rehabilitation with Nonlinearities Influences. *Int. J. Environ. Sci.* **2025**, *11*, 2890–2906. [CrossRef]
61. Sun, Z.; Li, F.; Wang, G.; Liu, Y.; Lian, Y.; Liu, K. A novel RBF neural network-based iterative learning control for lower limb rehabilitation robot with strong robustness. In *Proceedings of the 2019 Chinese Control Conference (CCC)*; IEEE: Piscataway, NJ, USA, 2019; pp. 4454–4459.
62. Arefeen, A.; Xiang, Y. Artificial neural network-based control of powered knee exoskeletons for lifting tasks: Design and experimental validation. *Robotica* **2024**, *42*, 2949–2968. [CrossRef]
63. Luo, S.; Androwis, G.; Adamovich, S.; Nunez, E.; Su, H.; Zhou, X. Robust walking control of a lower limb rehabilitation exoskeleton coupled with a musculoskeletal model via deep reinforcement learning. *J. Neuroeng. Rehabil.* **2023**, *20*, 34. [CrossRef] [PubMed]
64. Liu, X.; Wang, Q. Real-time locomotion mode recognition and assistive torque control for unilateral knee exoskeleton on different terrains. *IEEE/ASME Trans. Mechatron.* **2020**, *25*, 2722–2732. [CrossRef]
65. Zou, C.; Zeng, C.; Huang, R.; Peng, Z.; Zhang, J.; Cheng, H. Online gait learning with assist-as-needed control strategy for post-stroke rehabilitation exoskeletons. *Robotica* **2024**, *42*, 319–331. [CrossRef]
66. Choi, J.; Kim, H.; Choi, J.; Lee, J.M.; Choi, T.; Kim, S.-J.; Chun, M.H. EMG-Based Gait Speed Control of a Lower-limb Exoskeleton for Gait Rehabilitation: A Proof-of-Concept Study with Post-stroke Chronic Hemiparetic Patients. *Int. J. Precis. Eng. Manuf.* **2025**, *26*, 3059–3067. [CrossRef]
67. Cai, V.A.D.; Bidaud, P.; Hayward, V.; Gosselin, F.; Desailly, E. Self-adjusting, isostatic exoskeleton for the human knee joint. In *Proceedings of the 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*; IEEE: Piscataway, NJ, USA, 2011; pp. 612–618.
68. Witte, K.A.; Fatschel, A.M.; Collins, S.H. Design of a lightweight, tethered, torque-controlled knee exoskeleton. In *Proceedings of the 2017 International Conference on Rehabilitation Robotics (ICORR)*; IEEE: Piscataway, NJ, USA, 2017; pp. 1646–1653.
69. Wang, J.; Li, X.; Huang, T.-H.; Yu, S.; Li, Y.; Chen, T.; Carriero, A.; Oh-Park, M.; Su, H. Comfort-centered design of a lightweight and backdrivable knee exoskeleton. *IEEE Robot. Autom. Lett.* **2018**, *3*, 4265–4272. [CrossRef]
70. Yu, S.; Huang, T.-H.; Di Lallo, A.; Zhang, S.; Wang, T.; Fu, Q.; Su, H. Bio-inspired design of a self-aligning, lightweight, and highly-compliant cable-driven knee exoskeleton. *Front. Hum. Neurosci.* **2022**, *16*, 1018160. [CrossRef] [PubMed]
71. Brunet, M.; Pétriaux, M.; Di Meglio, F.; Petit, N. Enabling safe walking rehabilitation on the exoskeleton Atalante: Experimental results. In *Proceedings of the 2023 IEEE International Conference on Robotics and Automation (ICRA)*; IEEE: Piscataway, NJ, USA, 2023; pp. 12652–12658.
72. Tian, J.; Yuan, L.; Xiao, W.; Ran, T.; He, L. Trajectory following control of lower limb exoskeleton robot based on Udwadia–Kalaba theory. *J. Vib. Control* **2022**, *28*, 3383–3396. [CrossRef]
73. Jin, S.; Liu, B.; Wang, Z. A Bionic Knee Exoskeleton Design with Variable Stiffness via Rope-Based Artificial Muscle Actuation. *Biomimetics* **2025**, *10*, 424. [CrossRef] [PubMed]
74. Chen, J.; Hochstein, J.; Kim, C.; Tucker, L.; Hammel, L.E.; Damiano, D.L.; Bulea, T.C. A Pediatric Knee Exoskeleton with Real-Time Adaptive Control for Overground Walking in Ambulatory Individuals with Cerebral Palsy. *Front. Robot. AI* **2021**, *8*, 702137. [CrossRef] [PubMed]
75. Long, Y.; Du, Z.; Cong, L.; Wang, W.; Zhang, Z.; Dong, W. Active disturbance rejection control based human gait tracking for lower extremity rehabilitation exoskeleton. *ISA Trans.* **2017**, *67*, 389–397. [CrossRef] [PubMed]
76. Long, Y.; Peng, Y. Design and control of a quasi-direct drive actuated knee exoskeleton. *J. Bionic Eng.* **2022**, *19*, 678–687. [CrossRef]

77. Jin, X.; Zhu, S.; Zhu, X.; Chen, Q.; Zhang, X. Single-input adaptive fuzzy sliding mode control of the lower extremity exoskeleton based on human–robot interaction. *Adv. Mech. Eng.* **2017**, *9*, 1687814016686665. [CrossRef]
78. Zhang, P.; Gao, X. Fuzzy adaptive sliding mode control of lower limb exoskeleton rehabilitation robot. *Hip* **2022**, *30*, 10.
79. Laubscher, C.A.; Goo, A.; Farris, R.J.; Sawicki, J.T. Hybrid impedance-sliding mode switching control of the indego explorer lower-limb exoskeleton in able-bodied walking. *J. Intell. Robot. Syst.* **2022**, *104*, 76. [CrossRef]
80. Al Rezage, G.; Tokhi, M.O. Fuzzy PID control of lower limb exoskeleton for elderly mobility. In *Proceedings of the 2016 IEEE International Conference on Automation, Quality and Testing, Robotics (AQTR)*; IEEE: Piscataway, NJ, USA, 2016; pp. 1–6.
81. Asl, H.J.; Narikiyo, T.; Kawanishi, M. Neural network-based bounded control of robotic exoskeletons without velocity measurements. *Control Eng. Pract.* **2018**, *80*, 94–104. [CrossRef]
82. Hsu, L.; Cunha, J.P.V. Chattering is a persistent problem in classical and modern sliding mode control. In *Proceedings of the 2022 16th International Workshop on Variable Structure Systems (VSS)*; IEEE: Piscataway, NJ, USA, 2022; pp. 101–108.
83. Gambhire, S.; Kishore, D.R.; Londhe, P.; Pawar, S. Review of sliding mode based control techniques for control system applications. *Int. J. Dyn. Control* **2021**, *9*, 363–378. [CrossRef]
84. Utkin, V. Variable structure systems with sliding modes. *IEEE Trans. Autom. Control* **1977**, *22*, 212–222. [CrossRef]
85. Edwards, C.; Spurgeon, S. *Sliding Mode Control: Theory and Applications*; CRC Press: Boca Raton, FL, USA, 1998.
86. Wu, L.; Liu, J.; Vazquez, S.; Mazumder, S.K. Sliding mode control in power converters and drives: A review. *IEEE/CAA J. Autom. Sin.* **2021**, *9*, 392–406. [CrossRef]
87. Ouassaid, M.; Maaroufi, M.; Cherkaoui, M. Observer-based nonlinear control of power system using sliding mode control strategy. *Electr. Power Syst. Res.* **2012**, *84*, 135–143. [CrossRef]
88. Incremona, G.P.; Ferrara, A.; Magni, L. MPC for robot manipulators with integral sliding modes generation. *IEEE/ASME Trans. Mechatron.* **2017**, *22*, 1299–1307. [CrossRef]
89. Hashem Zadeh, S.M.; Khorashadizadeh, S.; Fateh, M.M.; Hadadzarif, M. Optimal sliding mode control of a robot manipulator under uncertainty using PSO. *Nonlinear Dyn.* **2016**, *84*, 2227–2239. [CrossRef]
90. Mat-Noh, M.; Mohd-Mokhtar, R.; Arshad, M.; Zain, Z.M.; Khan, Q. Review of sliding mode control application in autonomous underwater vehicles. *Indian J. Geo-Mar. Sci.* **2019**, *48*, 973–984.
91. Oh, K.; Seo, J. Development of a Sliding-Mode-Control-Based Path-Tracking Algorithm with Model-Free Adaptive Feedback Action for Autonomous Vehicles. *Sensors* **2023**, *23*, 405. [CrossRef] [PubMed]
92. Mancini, M.; Bloise, N.; Capello, E.; Punta, E. Sliding mode control techniques and artificial potential field for dynamic collision avoidance in rendezvous maneuvers. *IEEE Control Syst. Lett.* **2019**, *4*, 313–318. [CrossRef]
93. Komurcugil, H.; Biricik, S.; Bayhan, S.; Zhang, Z. Sliding mode control: Overview of its applications in power converters. *IEEE Ind. Electron. Mag.* **2020**, *15*, 40–49. [CrossRef]
94. Suleiman, H.U.; Mu'azu, M.B.; Zarma, T.A.; Salawudeen, A.T.; Thomas, S.; Galadima, A.A. Methods of chattering reduction in sliding mode control: A case study of ball and plate system. In *Proceedings of the 2018 IEEE 7th International Conference on Adaptive Science & Technology (ICAST)*; IEEE: Piscataway, NJ, USA, 2018; pp. 1–8.
95. Nemati, H.; Bando, M.; Hokamoto, S. Chattering attenuation sliding mode approach for nonlinear systems. *Asian J. Control* **2017**, *19*, 1519–1531. [CrossRef]
96. Hasan, S.; Dhingra, A.K. Development of a sliding mode controller with chattering suppressor for human lower extremity exoskeleton robot. *Results Control Optim.* **2022**, *7*, 100123. [CrossRef]
97. Mezghani Ben Romdhane, N.; Damak, T. Higher order sliding mode control of uncertain robot manipulators. In *Advances and Applications in Sliding Mode Control Systems*; Springer International Publishing: Cham, Switzerland, 2015; Volume 576, pp. 327–352.
98. Vyas, D.R.V.; Markana, A.M. Setpoint tracking control using modified Higher Order Sliding Mode Control: Application to robotic manipulator. In Proceedings of the ICTEA: International Conference on Thermal Engineering, Gandhinagar, India, 23–26 February 2019.
99. Sami, I.; Ullah, S.; Amin, S.U.; Al-Durra, A.; Ullah, N.; Ro, J. Convergence enhancement of super-twisting sliding mode control using artificial neural network for DFIG-based wind energy conversion systems. *IEEE Access* **2022**, *10*, 97625–97641. [CrossRef]
100. Pham, D.-A.; Ahn, J.-K.; Han, S.-H. Application of Improved Sliding Mode and Artificial Neural Networks in Robot Control. *Appl. Sci.* **2024**, *14*, 5304. [CrossRef]
101. Belkheir, A.; Mellouli, E.M. Controlling a two-link robot using sliding mode control combined with neural network. *Sens. Transducers* **2023**, *261*, 33–40.
102. Boiko, I. Chattering in Mechanical Systems Under Sliding-Mode Control. In *Sliding-Mode Control and Variable-Structure Systems: The State of the Art*; Springer: Berlin/Heidelberg, Germany, 2023; pp. 337–356.
103. Wani, Z.R.; Tantray, M.; Farsangi, E.N.; Nikitas, N.; Noori, M.; Samali, B.; Yang, T. A critical review on control strategies for structural vibration control. *Annu. Rev. Control* **2022**, *54*, 103–124. [CrossRef]
104. Hamza, M.F.; Abdullahi, A.M.; Alqahtani, A.; Rokbani, N. Hybrid Sliding Mode Control with Integral Resonant Control for Chattering Reduction in a 3-DOF Lower-Limb Exoskeleton Rehabilitation. *Appl. Sci.* **2026**, *16*, 410. [CrossRef]

105. Wu, H.; Jia, T.; Li, N.; Wu, J.; Yan, L. Study on the control algorithm for lower limb exoskeleton based on ADAMS/Simulink co-simulation. *J. Vibroeng.* **2017**, *19*, 2976–2986. [CrossRef]
106. Luo, Y.; Wang, C.; Wang, Z.; Ma, Y.; Wu, X. Comparision of different control algorithms for a knee exoskeleton. In *Proceedings of the 2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV)*; IEEE: Piscataway, NJ, USA, 2018; pp. 585–590.
107. Ashmi, M.; Anila, M.; Sivanandan, K. Comparison of SMC and PID controllers for pneumatically powered knee orthosis. *J. Control Autom. Electr. Syst.* **2021**, *32*, 1153–1163. [CrossRef]
108. Cruz-Cortes, A.; Ballesteros, M.; Cruz-Ortiz, D. Development of a lower limb robotic exoskeleton for mobilization of pediatric users. In *Proceedings of the 2025 11th International Conference on Control, Decision and Information Technologies (CoDIT)*; IEEE: Piscataway, NJ, USA, 2025; pp. 1025–1030.
109. Yuan, T.; Zhang, C.; Yi, F.; Lv, P.; Zhang, M.; Li, S. RBFNN-Based Adaptive Integral Sliding Mode Feedback and Feedforward Control for a Lower Limb Exoskeleton Robot. *Electronics* **2024**, *13*, 1043. [CrossRef]
110. Liao, Y.; Zhou, Z.; Wang, Q. BioKEX: A bionic knee exoskeleton with proxy-based sliding mode control. In *Proceedings of the 2015 IEEE International Conference on Industrial Technology (ICIT)*; IEEE: Piscataway, NJ, USA, 2015; pp. 125–130.
111. Centeno-Barreda, D.; Salazar-Cruz, S.; López-Gutiérrez, R.; Rosales-Luengas, Y.; Lozano, R. Lower limb exoskeleton for gait rehabilitation with adaptive nonsingular sliding mode control. *Robotica* **2024**, *42*, 3819–3838. [CrossRef]
112. Madani, T.; Daachi, B.; Djouani, K. Non-singular terminal sliding mode controller: Application to an actuated exoskeleton. *Mechatronics* **2016**, *33*, 136–145. [CrossRef]
113. Hernández, J.H.; Cruz, S.S.; López-Gutiérrez, R.; González-Mendoza, A.; Lozano, R. Robust nonsingular fast terminal sliding-mode control for sit-to-stand task using a mobile lower limb exoskeleton. *Control Eng. Pract.* **2020**, *101*, 104496. [CrossRef]
114. Narayan, J.; Abbas, M.; Patel, B.; Dwivedy, S.K. A singularity-free terminal sliding mode control of an uncertain paediatric exoskeleton system. In *Proceedings of the 2022 5th International Conference on Advanced Systems and Emergent Technologies (IC_ASET)*; IEEE: Piscataway, NJ, USA, 2022; pp. 198–203.
115. Zhu, X.; Liu, J.; Zhang, F.; Shen, X.; Chen, G.; Wu, X.; Cao, W. Trajectory Tracking Control of a Pediatric Lower Limb Gait Rehabilitation Exoskeleton Based on Nonsingular Fast Terminal Sliding Mode Control. *J. Phys. Conf. Ser.* **2025**, *3101*, 012006. [CrossRef]
116. Narayan, J.; Dwivedy, S.K. Robust gait tracking control of a pediatric exoskeleton system: An adaptive non-singular fast terminal sliding mode approach. In *Proceedings of the 2023 9th International Conference on Control, Decision and Information Technologies (CoDIT)*; IEEE: Piscataway, NJ, USA, 2023; pp. 2337–2341.
117. Narayan, J.; Abbas, M.; Dwivedy, S.K. Robust non-singular fast terminal sliding mode gait tracking control of a pediatric exoskeleton. In *Proceedings of the 2023 5th International Conference on Bio-Engineering For Smart Technologies (BioSMART)*; IEEE: Piscataway, NJ, USA, 2023; pp. 1–4.
118. Narayan, J.; Abbas, M.; Patel, B.M.; Jhunjhunwala, S.; Dwivedy, S.K. Improved Fast Terminal Sliding Mode Control for a Pediatric Gait Exoskeleton System: Theory and Experimental Results. In *Proceedings of the 2023 6th International Conference on Advances in Robotics*; ACM: New York, NY, USA, 2023; pp. 1–6.
119. Han, S.; Wang, H.; Tian, Y. Model-free based adaptive nonsingular fast terminal sliding mode control with time-delay estimation for a 12 DOF multi-functional lower limb exoskeleton. *Adv. Eng. Softw.* **2018**, *119*, 38–47. [CrossRef]
120. Ahmed, S.; Wang, H.; Tian, Y. Model-free control using time delay estimation and fractional-order nonsingular fast terminal sliding mode for uncertain lower-limb exoskeleton. *J. Vib. Control* **2018**, *24*, 5273–5290. [CrossRef]
121. Cao, S.-B.; Cao, G.-Z.; Zhang, Y.-P.; Ling, Z.-Q.; He, B.-B.; Huang, S.-D. Fast-terminal sliding mode control based on dynamic boundary layer for lower limb exoskeleton rehabilitation robot. In *Proceedings of the 2021 IEEE 11th Annual International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER)*; IEEE: Piscataway, NJ, USA, 2021; pp. 453–458.
122. Mokhtari, M.; Taghizadeh, M.; Ghaf-Ghanbari, P. Adaptive second-order sliding model-based fault-tolerant control of a lower-limb exoskeleton subject to tracking the desired trajectories augmented by CPG algorithm. *J. Braz. Soc. Mech. Sci. Eng.* **2022**, *44*, 423. [CrossRef]
123. Sun, Z.; Qiu, J.; Zhu, J.; Li, S. A composite position control of flexible lower limb exoskeleton based on second-order sliding mode. *Nonlinear Dyn.* **2023**, *111*, 1657–1666. [CrossRef]
124. Mefoued, S. A second order sliding mode control and a neural network to drive a knee joint actuated orthosis. *Neurocomputing* **2015**, *155*, 71–79. [CrossRef]
125. Zhang, M.; Huang, J.; Cao, Y.; Xiong, C.-H.; Mohammed, S. Echo state network-enhanced super-twisting control of passive gait training exoskeleton driven by pneumatic muscles. *IEEE/ASME Trans. Mechatron.* **2022**, *27*, 5107–5118. [CrossRef]
126. Zhang, W.; Ji, P.; Song, P.; Liu, H.; Li, Q.; Mo, X. Design and Implement of a Super-Twisting ESO-Based Impedance Control for Lower Limb Exoskeleton. In *Proceedings of the Mechatronics and Automation Technology: Proceedings of the 3rd International Conference (ICMAT 2024), Wuhan, China, 25–26 October 2024*; SAGE Publications: London, UK, 2024; pp. 531–539.

127. Mbarek, H.B.H.; Saidi, I. Super-Twisting Sliding Mode Control for Improved Trajectory Tracking in Lower-Limb Rehabilitation Exoskeleton. In *Proceedings of the 2025 IEEE International Conference on Advanced Systems and Emergent Technologies (IC_ASET)*; IEEE: Piscataway, NJ, USA, 2025; pp. 1–6.
128. Rakhtala, S.M. Adaptive gain super twisting algorithm to control a knee exoskeleton disturbed by unknown bounds. *Int. J. Dyn. Control* **2021**, *9*, 711–726. [CrossRef]
129. Zhang, M.; Huang, J.; Cao, Y.; Zhang, H.-T. Super twisting control of passive gait training exoskeleton driven by pneumatic muscles. In *Proceedings of the 2019 International Symposium on Micro-NanoMechatronics and Human Science (MHS)*; IEEE: Piscataway, NJ, USA, 2019; pp. 1–7.
130. Mokhtari, M.; Taghizadeh, M.; Mazare, M. Impedance control based on optimal adaptive high order super twisting sliding mode for a 7-DOF lower limb exoskeleton. *Meccanica* **2021**, *56*, 535–548. [CrossRef]
131. Zhang, J.; Gao, W.; Guo, Q. Extended State Observer-Based Sliding Mode Control Design of Two-DOF Lower Limb Exoskeleton. *Actuators* **2023**, *12*, 402. [CrossRef]
132. Abdullahi, A.M.; Chaichaowarat, R. Sensorless estimation of human joint torque for robust tracking control of lower-limb exoskeleton assistive gait rehabilitation. *J. Sens. Actuator Netw.* **2023**, *12*, 53. [CrossRef]
133. Jia, H.; Xia, D.; Hao, L. Research of smc-ude control for lower limb wearable exoskeleton Robot. In *Proceedings of the 2023 42nd Chinese Control Conference (CCC)*; IEEE: Piscataway, NJ, USA, 2023; pp. 8026–8031.
134. Mefoued, S.; Belkhiat, D.E.C. A robust control scheme based on sliding mode observer to drive a knee-exoskeleton. *Asian J. Control* **2019**, *21*, 439–455. [CrossRef]
135. Mohammed, S.; Huo, W.; Huang, J.; Rifaï, H.; Amirat, Y. Nonlinear disturbance observer based sliding mode control of a human-driven knee joint orthosis. *Robot. Auton. Syst.* **2016**, *75*, 41–49. [CrossRef]
136. Alawad, N.A.; Humaidi, A.J.; Alaraji, A.S. Sliding mode-based active disturbance rejection control of assistive exoskeleton device for rehabilitation of disabled lower limbs. *An. Acad. Bras. Ciênc.* **2023**, *95*, e20220680. [CrossRef] [PubMed]
137. Qin, M.; Lian, L.; Dang, X.; Wang, B.; Wang, H. Active disturbance rejection with continous sliding mode control for lower limb rehabilitation exoskeleton. In *Proceedings of the 2025 10th International Conference on Automation, Control and Robotics Engineering (CACRE)*; IEEE: Piscataway, NJ, USA, 2025; pp. 60–64.
138. Chen, C.-F.; Du, Z.-J.; He, L.; Wang, J.-Q.; Wu, D.-M.; Dong, W. Active disturbance rejection with fast terminal sliding mode control for a lower limb exoskeleton in swing phase. *IEEE Access* **2019**, *7*, 72343–72357. [CrossRef]
139. Narayan, J.; Dwivedy, S.K. Pediatric gait training using a lower-limb exoskeleton with adaptive finite-time sliding mode control scheme: An experimental study. *Trans. Inst. Meas. Control* **2025**, *47*, 1438–1454. [CrossRef]
140. Kenas, F.; Saadia, N.; Ababou, A.; Ababou, N. Model-free based adaptive finite time control with multilayer perceptron neural network estimation for a 10 DOF lower limb exoskeleton. *Int. J. Adapt. Control Signal Process.* **2024**, *38*, 696–730. [CrossRef]
141. Liu, J.; Zhang, Y.; Wang, J.; Chen, W. Adaptive sliding mode control for a lower-limb exoskeleton rehabilitation robot. In *Proceedings of the 2018 13th IEEE Conference on Industrial Electronics and Applications (ICIEA)*; IEEE: Piscataway, NJ, USA, 2018; pp. 1481–1486.
142. Pérez-San Lázaro, R.; Salgado, I.; Chairez, I. Adaptive sliding-mode controller of a lower limb mobile exoskeleton for active rehabilitation. *ISA Trans.* **2021**, *109*, 218–228. [CrossRef] [PubMed]
143. Liu, X.; Zhang, S.; Liu, S.; Xu, K.; Yao, B. Adaptive backstepping sliding mode control for a hydraulic knee exoskeleton robot. In *Proceedings of the 2020 2nd International Conference on Artificial Intelligence, Robotics and Control*; ACM: New York, NY, USA, 2020; pp. 43–48.
144. Hasan, S.K.; Alam, N. Biomechanical Design and Adaptive Sliding Mode Control of a Human Lower Extremity Exoskeleton for Rehabilitation Applications. *Robotics* **2025**, *14*, 146. [CrossRef]
145. Faraj, M.A.; Maalej, B.; Derbel, N. Fractional order based controllers for lower limb exoskeleton in contact environments. In *Proceedings of the 2023 20th International Multi-Conference on Systems, Signals & Devices (SSD)*; IEEE: Piscataway, NJ, USA, 2023; pp. 705–710.
146. Ahmed, S.; Wang, H.; Tian, Y. Robust adaptive fractional-order terminal sliding mode control for lower-limb exoskeleton. *Asian J. Control* **2019**, *21*, 473–482. [CrossRef]
147. Chen, N.; Wang, J.; Yun, L.; Zou, J.; Zhang, C. Research on Trajectory Tracking Control of Lower Limb Exoskeleton Based on Fractional Order Sliding Mode and Disturbance Observer. *Adv. Theory Simul.* **2025**, *8*, e00849. [CrossRef]
148. Nhu, T.Q.; Thinh, N.D. A new novel fractional optimal sliding mode control for lower-limb exoskeleton. In *Proceedings of the 2019 International Conference on System Science and Engineering (ICSSE)*; IEEE: Piscataway, NJ, USA, 2019; pp. 410–413.
149. Zhou, Y.; Sun, Z.; Chen, B.; Huang, G.; Wu, X.; Wang, T. Humangaittrackingforrehabilitation exoskeleton: Adap-tive fractional order sliding mode control approach. *Intell. Robot.* **2023**, *3*, 95–112. [CrossRef]
150. Faraj, M.A.; Maalej, B.; Derbel, N.; Naifar, O. Adaptive Fractional-Order Super-Twisting Sliding Mode Controller for Lower Limb Rehabilitation Exoskeleton in Constraint Circumstances Based on the Grey Wolf Optimization Algorithm. *Math. Probl. Eng.* **2023**, *2023*, 9641673. [CrossRef]

151. Znidi, A.; Nouri, A.S.; Derbel, N. Trajectory Tracking of Lower Limb Exoskeletons using Fractional Order Sliding Mode Control. In *Proceedings of the 2023 IEEE International Workshop on Mechatronic Systems Supervision (IW_MSS)*; IEEE: Piscataway, NJ, USA, 2023; pp. 1–6.
152. Jallouli-Khlif, R.; Abdelhedi, F.; Zayane, C.; Nouri, A.S.; Derbel, N. Robust sliding mode control based on fractional order reaching law for rehabilitation robots. *IEEE Access* **2025**, *13*, 75744–75753. [CrossRef]
153. He, H.; Xi, R.; Gong, Y. Performance analysis of a robust controller with neural network algorithm for compliance Tendon–Sheath actuation lower limb exoskeleton. *Machines* **2022**, *10*, 1064. [CrossRef]
154. Li, J.; Jiang, H.; Gao, M.; Li, S.; Wang, Z.; Pang, Z.; Zhang, Y.; Jiao, Y. Research on Iterative Learning Method for Lower Limb Exoskeleton Rehabilitation Robot Based on RBF Neural Network. *Appl. Sci.* **2025**, *15*, 6053. [CrossRef]
155. Li, X.; Li, J.; Wang, Y.; Wang, K.; Cui, B.; Yuan, Y. Research on a RBF-based compliance control method of lower limb exoskeleton robots. *Intell. Serv. Robot.* **2025**, *18*, 1249–1264. [CrossRef]
156. Zhao, Y.; Li, S.; Han, J.; Huo, W. Robust Adaptive Neural Force Control of a SEA-Based Knee Exoskeleton With Low Impedance. *IEEE/ASME Trans. Mechatron.* **2025**, *30*, 5352–5363. [CrossRef]
157. Wang, Z.; Zhu, S.; Chen, Q.; Zhang, X.; Song, Y. Sliding mode control of electro-hydraulic servo system for lower-limb exoskeleton based on RBF neural network. In *Proceedings of the 2015 IEEE 10th Conference on Industrial Electronics and Applications (ICIEA)*; IEEE: Piscataway, NJ, USA, 2015; pp. 79–83.
158. Zhang, P.; Zhang, J.; Zhang, Z. Design of RBFNN-based adaptive sliding mode control strategy for active rehabilitation robot. *IEEE Access* **2020**, *8*, 155538–155547. [CrossRef]
159. Zhou, F.; Li, J.; Wang, J. RBFNN-based trajectory tracking and motion synchronization for mobile rehabilitation robot exoskeleton. In *Proceedings of the 2022 IEEE International Conference on Mechatronics and Automation (ICMA)*; IEEE: Piscataway, NJ, USA, 2022; pp. 1505–1512.
160. Eshetu, B.; Seid, S. Modeling and design of ANFIS dynamic sliding mode controller for a knee orthosis of hemiplegia. *Appl. Bionics Biomech.* **2023**, *2023*, 9953957. [CrossRef]
161. Maalej, B.; Medhaffar, H.; Chemori, A.; Derbel, N. A Fuzzy Sliding Mode Controller for Reducing Torques Applied to a Rehabilitation Robot. In *Proceedings of the 2020 17th International Multi-Conference on Systems, Signals & Devices (SSD)*; IEEE: Piscataway, NJ, USA, 2020; pp. 740–746.
162. Gebrecherkos, T.H.; Berhe, A.G.; Gurusamy, S.; Abdissa, C.M. Fuzzy Sliding Mode Control for Dynamic Walking Assistance in Lower Limb Exoskeletons. *IEEE Access* **2025**, *13*, 161235–161249. [CrossRef]
163. Liu, M.; Zhang, C.; Zhu, X.C. Design of fuzzy adaptive synovial control system for lower limb exoskeleton. In *Proceedings of the International Conference on Intelligent Equipment and Special Robots (ICIESR 2021)*; SPIE: Bellingham, WA, USA, 2021; p. 121270I.
164. Li, Z.; Dong, W.; Wang, L.; Chen, C.; Wang, J.; Du, Z. Lower limb exoskeleton hybrid phase control based on fuzzy gain sliding mode controller. In *Proceedings of the 2018 2nd International Conference on Robotics and Automation Sciences (ICRAS)*; IEEE: Piscataway, NJ, USA, 2018; pp. 1–5.
165. Waheed, Z.A.; Humaidi, A.J. Whale Optimization Algorithm Enhances the Performance of Knee-Exoskeleton System Controlled by SMC. *IRAQI J. Comput. Commun. Control Syst. Eng.* **2023**, *23*, 125–135. [CrossRef]
166. Long, Y.; Du, Z.-j.; Wang, W.-d.; Dong, W. Robust sliding mode control based on GA optimization and CMAC compensation for lower limb exoskeleton. *Appl. Bionics Biomech.* **2016**, *2016*, 5017381. [CrossRef] [PubMed]
167. Cao, Y.; Huang, J.; Huang, Z.; Tu, X.; Mohammed, S. Optimizing control of passive gait training exoskeleton driven by pneumatic muscles using switch-mode firefly algorithm. *Robotica* **2019**, *37*, 2087–2103. [CrossRef]
168. Xie, Z.; Li, Y.; Tian, B.; Liu, Y.; Zhang, C.; Guo, H. Adaptive sliding mode controller based on improved Sparrow search algorithm for tracking control of human lower limb exoskeleton. *ISA Trans.* **2025**, *166*, 250–265. [CrossRef] [PubMed]
169. Wong Sang, M.; Narayan, J. Reinforcement Learning-Based Finite-Time Sliding-Mode Control in a Human-in-the-Loop Framework for Pediatric Gait Exoskeleton. *Machines* **2025**, *13*, 668. [CrossRef]
170. Fuentes-Alvarez, R.; Hernandez, J.H.; Matehuala-Moran, I.; Alfaro-Ponce, M.; Lopez-Gutierrez, R.; Salazar, S.; Lozano, R. Assistive robotic exoskeleton using recurrent neural networks for decision taking for the robust trajectory tracking. *Expert Syst. Appl.* **2022**, *193*, 116482. [CrossRef]
171. Sun, Z.; Chai, T.; Chen, B.; Wang, H.; Zheng, J.-C.; Man, Z.-H. Non-Force-Sensing Variable Admittance Control of Lower Limb Rehabilitation Exoskeleton Robots Using Class $\kappa\infty$ Function-Based Adaptive Sliding Mode. *IEEE Trans. Autom. Sci. Eng.* **2025**, *22*, 20995–21009. [CrossRef]
172. Torabi, M.; Sharifi, M.; Vossoughi, G.R. Robust Adaptive Sliding Mode Admittance Control of Exoskeleton Rehabilitation Robots. *Sci. Iran.* **2017**, *25*, 2628–2642. [CrossRef]
173. Kumar, S.; Narayan, J.; Prakash, K.; Dwivedy, S.K. Combining Variable Admittance with Finite-Time Sliding Mode Control for a Pediatric Gait Exoskeleton: A Human-in-the-Loop Framework. In *Proceedings of the 2025 Eleventh Indian Control Conference (ICC)*; IEEE: Piscataway, NJ, USA, 2025; pp. 672–677.

174. Narayan, J.; Abbas, M.; Pratap, S.; Bharti, R.R.; Dwivedy, S.K. Integrating Robust Gait Tracking Control and Variable Admittance Model for Pediatric Exoskeleton: An 'Assist-as-Needed' Framework. *IFAC-PapersOnLine* **2024**, *57*, 113–118. [CrossRef]
175. Zhang, F.; Wang, T.; Zhang, L.; Shi, E.; Wang, C.; Li, N.; Lu, Y.; Zhang, B. Sliding-mode control based on prescribed performance function and its application to a SEA-Based lower limb exoskeleton. *Front Robot AI* **2025**, *12*, 1534040. [CrossRef] [PubMed]
176. Song, J.; Zhu, A.; Tu, Y.; Zhang, X.; Cao, G. Novel design and control of a crank-slider series elastic actuated knee exoskeleton for compliant human–robot interaction. *IEEE/ASME Trans. Mechatron.* **2022**, *28*, 531–542. [CrossRef]
177. Wang, J.; Liu, J.; Zhang, G.; Guo, S. Periodic event-triggered sliding mode control for lower limb exoskeleton based on human–robot cooperation. *ISA Trans.* **2022**, *123*, 87–97. [CrossRef] [PubMed]
178. Li, M.; Hu, Y.; Feng, W.; Wang, C.; Wu, X. Adaptive Sliding Mode Control for Biped Robots with sEMG Signals. In *Proceedings of the 2018 IEEE International Conference on Cyborg and Bionic Systems (CBS)*; IEEE: Piscataway, NJ, USA, 2018; pp. 656–661.
179. Llorente-Vidrio, D.; Pérez-San Lázaro, R.; Ballesteros, M.; Salgado, I.; Cruz-Ortiz, D.; Chairez, I. Event driven sliding mode control of a lower limb exoskeleton based on a continuous neural network electromyographic signal classifier. *Mechatronics* **2020**, *72*, 102451. [CrossRef]
180. Zhang, P.; Gao, X.; Miao, M.; Zhao, P. Design and Control of a Lower Limb Rehabilitation Robot Based on Human Motion Intention Recognition with Multi-Source Sensor Information. *Machines* **2022**, *10*, 1125. [CrossRef]
181. Xu, W.X.; Cao, G.Z.; Zhang, Y.P.; Chen, J.C.; Tan, D.P.; Ling, Z.Q. Adaptive backstepping sliding mode control of lower limb exoskele-ton robot based on combined double power reaching law. In *Proceedings of the 2022 12th International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER)*; IEEE: Piscataway, NJ, USA, 2022; pp. 1095–1100.
182. Mokhtari, M.; Taghizadeh, M.; Ghanbari, P.G. Fault tolerant control based on backstepping nonsingular terminal integral sliding mode and impedance control for a lower limb exoskeleton. *Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci.* **2022**, *236*, 2698–2713. [CrossRef]
183. Tu, X.; Li, J.; Li, J.; Su, C.; Zhang, S.; Li, H.; Cao, J.; He, J. Model-Based Hybrid Cooperative Control of Hip-Knee Exoskeleton and FES Induced Ankle Muscles for Gait Rehabilitation. *Int. J. Pattern Recognit. Artif. Intell.* **2017**, *31*, 1759019. [CrossRef]
184. Khamar, M.; Edrisi, M. Designing a backstepping sliding mode controller for an assistant human knee exoskeleton based on nonlinear disturbance observer. *Mechatronics* **2018**, *54*, 121–132. [CrossRef]
185. Mokhtari, M.; Taghizadeh, M.; Mazare, M. Active fault tolerant control based on adaptive back-stepping nonsingular fast integral terminal sliding mode approach. *Amirkabir J. Mech. Eng.* **2021**, *53*, 3763–3782. [CrossRef]
186. Mokhtari, M.; Taghizadeh, M.; Mazare, M. Hybrid Adaptive Robust Control Based on CPG and ZMP for a Lower Limb Exoskeleton. *Robotica* **2020**, *39*, 181–199. [CrossRef]
187. Narayan, J.; Abbas, M.; Dwivedy, S.K. Design and validation of a pediatric gait assistance exoskeleton system with fast non-singular terminal sliding mode controller. *Med. Eng. Phys.* **2024**, *123*, 104080. [CrossRef] [PubMed]
188. Long, Y.; Peng, Y. Extended state observer-based nonlinear terminal sliding mode control with feedforward compensation for lower extremity exoskeleton. *IEEE Access* **2021**, *10*, 8643–8652. [CrossRef]
189. Gao, X.; Zhang, P.; Peng, X.; Zhao, J.; Liu, K.; Miao, M.; Zhao, P.; Luo, D.; Li, Y. Autonomous motion and control of lower limb exoskeleton rehabilitation robot. *Front. Bioeng. Biotechnol.* **2023**, *11*, 1223831. [CrossRef] [PubMed]
190. Faraj, M.A.; Maalej, B.; Derbel, N. Optimal sliding mode controller for lower limb rehabilitation exoskeleton in constrained environments. *Indones. J. Electr. Eng. Comput. Sci.* **2023**, *30*, 1458–1469. [CrossRef]
191. Zhang, Y.; Wang, J.; Li, W.; Wang, J.; Yang, P. A model-free control method for estimating the joint angles of the knee exoskeleton. *Adv. Mech. Eng.* **2018**, *10*, 1687814018807768. [CrossRef]
192. Narayan, J.; Bharti, R.R.; Dwivedy, S.K. Robust sliding mode control with reaching laws for a pediatric lower-limb exoskeleton system. In *Proceedings of the 2022 Second International Conference on Power, Control and Computing Technologies (ICPC2T)*; IEEE: Piscataway, NJ, USA, 2022; pp. 1–6.
193. Lee, T.; Lee, D.; Song, B.; Baek, Y.S. Design and control of a polycentric knee exoskeleton using an electro-hydraulic actuator. *Sensors* **2019**, *20*, 211. [CrossRef] [PubMed]
194. Zhao, W.; Song, A. Active motion control of a knee exoskeleton driven by antagonistic pneumatic muscle actuators. *Actuators* **2020**, *9*, 134. [CrossRef]
195. Lee, L.-W.; Li, I.-H.; Lu, L.-Y.; Hsu, Y.-B.; Chiou, S.-J.; Su, T.-J. Hardware development and safety control strategy design for a mobile rehabilitation robot. *Appl. Sci.* **2022**, *12*, 5979. [CrossRef]
196. Chen, L.; Wang, C.; Wang, J.; Song, X. Design of hybrid phase sliding mode control scheme for lower extremity exoskeleton. *Appl. Sci.* **2019**, *9*, 3754. [CrossRef]
197. Salcido, E.A.A.; Centeno-Barreda, D.; Rosales, Y.; Lopéz-Gutiérrez, R.; Salazar, S.; Lozano, R. Design of a lower limb exoskeleton: Robust control, simulation and experimental results. *Algorithms* **2023**, *16*, 449. [CrossRef]
198. Sun, Z.; Chen, W.; Chen, B.; Wang, H.; Zheng, J.; Man, Z. CPG-based gait planning and model-independent adaptive time-delay control for lower limb rehabilitation exoskeleton robots. *Control Theory Technol.* **2025**, *23*, 650–662. [CrossRef]

199. Su, Y.; Zhang, W.; Ding, X. Observer based sliding mode control for a knee exoskeleton. In *International Workshop on Medical and Service Robots*; Springer: Berlin/Heidelberg, Germany, 2021.
200. Lu, X.; Jia, S.; Chen, L.; Wang, X.; Han, Y. Trajectory tracking control of a hydraulic-tendon actuator with an application to the exoskeleton. *J. Vibroeng.* **2016**, *18*, 496–510. [CrossRef]
201. Liu, Y.; Peng, S.; Zhang, J.; Xie, K.; Lin, Z.; Liao, W.-H. Event-triggered sliding mode impulsive control for lower limb rehabilitation exoskeleton robot gait tracking. *Symmetry* **2023**, *15*, 224. [CrossRef]
202. Yuan, T.; Zhang, C.; Yi, F.; Lv, P.; Li, S.; Zhang, M. Adaptive position tracking control of the lower limb exoskeleton robot with an uncertain dynamic model. In *2023 IEEE 18th Conference on Industrial Electronics and Applications (ICIEA)*; IEEE: Piscataway, NJ, USA, 2023.
203. Zhao, J.; Yang, T.; Ma, Z.; Yang, C.; Wang, Z.; Xu, J. Design of MG modal space sliding mode control for lower limb exoskeleton robot driven by electrical actuators. *Mechatronics* **2021**, *78*, 102610. [CrossRef]
204. Zheng, L.; Boubaker, S.; Ramli, R.; Kamel, S.; Khamis, N.K.; Ghazali, M.H.M. Symmetry-Enhanced Intelligent Switching Control for Support-Swing Phase Transition in Robotic Exoskeleton. *Symmetry* **2025**, *17*, 1859. [CrossRef]
205. Chen, C.-F.; Du, Z.-J.; He, L.; Shi, Y.-J.; Wang, J.-Q.; Xu, G.-Q.; Zhang, Y.; Wu, D.-M.; Dong, W. Development and hybrid control of an electrically actuated lower limb exoskeleton for motion assistance. *IEEE Access* **2019**, *7*, 169107–169122. [CrossRef]
206. Li, J.; Wei, Y.; Yang, K.; Wang, J. A Control Method for Assisted Stair Climbing Exoskeleton Robot. In *2024 IEEE International Conference on Mechatronics and Automation (ICMA)*; IEEE: Piscataway, NJ, USA, 2024.
207. Cruz-Cortes, A.; Cruz-Ortiz, D.; Ballesteros, M. Robust control with restrictions for a six-DoF lower limb exoskeleton: A sliding mode approach. In *2024 12th International Conference on Control, Mechatronics and Automation (ICCMA)*; IEEE: Piscataway, NJ, USA, 2024.
208. Sun, Z.; Li, Z.; Zhou, Y.; Li, T.; Chen, B. Robust control of a 2-DOF lower limb exoskeleton rehabilitation robot using nonsingular terminal sliding mode. In *2022 IEEE 17th International Conference on Control & Automation (ICCA)*; IEEE: Piscataway, NJ, USA, 2022.
209. Liu, J.; Wang, J.; Zhang, G. Event-triggered sliding mode controller design for lower limb exoskeleton. In *2020 39th Chinese Control Conference (CCC)*; IEEE: Piscataway, NJ, USA, 2020.
210. Sitler, G.; Sardahi, Y.; Salem, A. Optimal Nonsingular Terminal Sliding Mode Control for Knee Replacement Exoskeletons. In *ASME International Mechanical Engineering Congress and Exposition*; American Society of Mechanical Engineers: New York, NY, USA, 2024.
211. Behnamgol, V.; Asadi, M.; Aphale, S.S.; Sohani, B. Recursive PID-NT Estimation-Based Second-Order SMC Strategy for Knee Exoskeleton Robots: A Focus on Uncertainty Mitigation. *Electronics* **2025**, *14*, 1455. [CrossRef]
212. Zhang, Z.; Qiu, S.; Liu, Y.; Yan, D.; Ming, D. Fusion Control of a Lower Limb Hybrid Neural Prosthesis Based on Model Predictive Control and Sliding Mode Control Strategies. In *2024 IEEE International Conference on Robotics and Biomimetics (ROBIO)*; IEEE: Piscataway, NJ, USA, 2024.
213. Wang, J.; Li, J.; Zhang, W.; Zhou, F. Research on trajectory tracking of lower limb exoskeleton rehabilitation robot based on sliding mode control. In *International Conference on Intelligent Robotics and Applications*; Springer: Berlin/Heidelberg, Germany, 2021.
214. Luo, Y.; Wang, C.; Wang, Z.; Ma, Y.; Wang, C.; Wu, X. Design and control for a compliant knee exoskeleton. In *2017 IEEE International Conference on Information and Automation (ICIA)*; IEEE: Piscataway, NJ, USA, 2017.
215. Zhu, A.; Tu, Y.; Zheng, W.; Shen, H.; Zhang, X. Adaptive control of man-machine interaction force for lower limb exoskeleton rehabilitation robot. In *2018 IEEE International Conference on Information and Automation (ICIA)*; IEEE: Piscataway, NJ, USA, 2018.
216. Yu, J.; Zhang, S.; Wang, A.; Li, W.; Ma, Z.; Yue, X. Humanoid control of lower limb exoskeleton robot based on human gait data with sliding mode neural network. *CAAI Trans. Intell. Technol.* **2022**, *7*, 606–616. [CrossRef]
217. Kenas, F.; Saadia, N.; Ababou, A.; Ababou, N. Model-free based adaptive BackStepping-Super Twisting-RBF neural network control with α-variable for 10 DOF lower limb exoskeleton: Model-free based adaptive BackSepping-Super Twisting. *Int. J. Intell. Robot. Appl.* **2024**, *8*, 122–148. [CrossRef]
218. Han, Y.; Liu, S.; Chang, J.; Sun, H.; Li, S.; Gao, H.; Jin, Z. Design and preliminary evaluation of a lower limb exoskeleton based on hydraulic actuator. *Ind. Robot. Int. J. Robot. Res. Appl.* **2024**, *51*, 44–57. [CrossRef]
219. Van, N.Q.; Phu, D.X. A new novel exponentical optimal sliding mode control and its application for lower-limb exoskeleton. In *2019 International Conference on System Science and Engineering (ICSSE)*; IEEE: Piscataway, NJ, USA, 2019.
220. Zhang, P.; Zhang, J. The Design and Evaluation of Complex Radial Basis Functions Network Adaptive Robust Variable Sliding Mode Controller for Stroke Rehabilitation Robot. In *2020 IEEE International Conference on Mechatronics and Automation (ICMA)*; IEEE: Piscataway, NJ, USA, 2020.
221. Faraj, M.A.; Maalej, B.; Derbel, N. Sliding mode control for lower limb rehabilitation exoskeleton contacting with Floor. In *2023 20th International Multi-Conference on Systems, Signals & Devices (SSD)*; IEEE: Piscataway, NJ, USA, 2023.

222. Cao, Y.; Huang, J.; Huang, Z.; Tu, X.; Ru, H.; Chen, C.; Huo, J. Dynamic model of exoskeleton based on pneumatic muscle actuators and experiment verification. In *2018 IEEE-RAS 18th International Conference on Humanoid Robots (Humanoids)*; IEEE: Piscataway, NJ, USA, 2018.
223. Khamar, M.; Edrisi, M.; Forghany, S. Designing a robust controller for a lower limb exoskeleton to treat an individual with crouch gait pattern in the presence of actuator saturation. *Isa Trans*. **2022**, *126*, 513–532. [CrossRef] [PubMed]
224. Hasan, S.; Dhingra, A.K. Performance verification of different control schemes in human lower extremity rehabilitation robot. *Results Control Optim*. **2021**, *4*, 100028. [CrossRef]
225. Zhong, B.; Cao, J.; Guo, K.; McDaid, A.; Peng, Y.; Miao, Q.; Xie, S.; Zhang, M. Fuzzy logic compliance adaptation for an assist-as-needed controller on the Gait Rehabilitation Exoskeleton (GAREX). *Robot. Auton. Syst*. **2020**, *133*, 103642. [CrossRef]
226. Hasan, S.; Dhingra, A.K. Biomechanical design and control of an eight DOF human lower extremity rehabilitation exoskeleton robot. *Results Control Optim*. **2022**, *7*, 100107. [CrossRef]

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