International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-23
© Cerebration Science Publishing
https://doi.org/10.70917/ijcisim-2026-1101
Article

A Comprehensive Review of Power-Assisted Exoskeletons: From Perception to Control Strategies

Guangyong Wu [1,2,*], Tianhong Luo [3], Alexey A. Khoreshok [2], Ilya V. Kozlov [2], Alexander N. Ermakov [2] and Qing Chen [1,2]

[1] School of Intelligent Manufacturing Engineering, Chongqing University of Arts and Sciences, Chongqing, 402160, China
[2] T. F. Gorbachev Kuzbass State Technical University, Kuzbass, 650000, Russia
[3] College of Information and Intelligent Manufacturing, Chongqing City Vocational College, Chongqing, 402160, China
* Correspondence author: wgyong2026@126.com

Abstract: Power-assisted exoskeletons represent a highly promising technology that can enhance human strength and improve productivity, with broad applications across military, industrial, construction, mining, and daily life domains. To provide natural and compliant assistance to the human body, an exoskeleton must accurately understand human motion intentions and rapidly make control decisions to drive joints to actively adapt to human movement. Over the past two decades, research on human motion intention sensing, understanding, and collaborative control strategies has been extensive. However, due to the complex, highly nonlinear interactions among humans, machines, and the environment—including physiological and random signal interference in perception, uncertain external forces, and sudden intention changes—no major breakthroughs have been achieved in the collaborative control of power-assisted exoskeletons. The existing review literature on this topic is relatively outdated. As a research contribution, this paper presents a comprehensive and systematic review from a critical perspective, classifying representative studies and related technologies across three key areas: the latest environmental-EMG-EEG-based human-robot interaction sensing and localization techniques, machine learning-based human motion intention recognition and prediction, and intelligent control strategies aimed at human-robot collaboration. From a macro perspective, the paper discussed existing challenges and unresolved issues across these three domains, while proposing forward-looking recommendations and potential research directions.

Keywords: Power-assisted exoskeletons, Motion intent recognition and prediction, Control strategies, Human-machine collaboration

1. Introduction

Exoskeletons are wearable intelligent robotic systems integrating advanced technologies from mechanics, materials, electronics, control, bionics, and robotics. Based on application, they are primarily classified into three categories [1]: 1) Strength-augmentation exoskeletons, designed to enhance physical capabilities such as strength, endurance, and mobility in healthy individuals for tasks like heavy lifting, long-distance load carriage, or operating heavy tools; 2) Mobility-assist exoskeletons, aiding elderly or disabled individuals in walking; and 3) Rehabilitation exoskeletons, supporting patients in performing therapeutic exercises. This paper focuses on the first two categories, with an emphasis on strength-augmentation exoskeletons.

The development of flexible exoskeletons to enhance human physical capabilities has long been a goal for researchers and laborers. From Lent’s conceptual proposal of exoskeleton technology in 1956

[2] to Mizen's first "human amplifier" in 1966 and General Electric engineers Mosher et al.'s Hardiman exoskeleton [3]—the first functional exoskeleton with practical significance—early research laid the foundation for exoskeleton development. However, due to technological limitations, Hardiman was bulky, poorly coordinated, and ultimately abandoned in 1971. Notably, pivotal control theories such as master-slave control and the Zero Moment Point (ZMP) balance principle emerged during this period. By the 1990s, advancements in electromechanical control and sensing revived exoskeleton research. Under the U.S. military's Enhanced Human Performance Exoskeleton (EHPA) program, milestones included BLEEX [4-5], XOS [6], HULC [7], MIT Exoskeleton [8], and Harvard's Soft Exosuit [9]. Among these, BLEEX pioneered sensitivity amplification control [10-11], enabling precise motion tracking, while XOS2 demonstrated agility sufficient for soccer [6]. In healthcare, HAL5 [12-13], the first commercially viable gait-assist exoskeleton using surface electromyography (sEMG) for motion intent recognition, was released in 2013, followed by ReWalk [14-15], Indego [16], eLEGs [17], Ekso [18], and the EU's MindWalker—the first exoskeleton incorporating a brain-computer interface (BCI) [19-20]. Applications have since expanded to industry, aerospace, and agriculture, including Fortis [21] (aircraft assembly), DSME Wearable Robot [22] (shipbuilding), NASA's X1 [23], Japan's Agri-Robot [24], and Shanghai's food-delivery exoskeleton HEMS-GS [25].

Over the past two decades, advancements in energy storage, actuation, sensing, communication, and control technologies have driven significant progress in exoskeleton research. Among these, rehabilitation and mobility-assist exoskeletons have achieved notable advancements due to their relatively fixed motion trajectories and stable operating speeds. In contrast, strength-augmentation exoskeletons face slower development due to the complexity of dynamic environments—such as frequent transitions between level ground, slopes, stairs, and other terrains—in real-world scenarios.

Strength-augmentation exoskeletons are typically designed for heavy-load tasks like carrying, lifting, and transporting, operating in close physical integration with the human body through wearable designs. This inherently defines their "Human-in-the-loop" characteristics, where ensuring safety, stability, human-machine coordination, and wearer comfort are unavoidable design objectives. It can be said that coordinated control is the main decisive factor in the availability of exoskeletons. On the one hand, it can ensure the safety of exoskeletons and avoid injury to the human body during the assistance process. On the other hand, it can improve the flexibility of joints and the comfort of wearing. As shown in Figure 1, to achieve more accurate human-computer interaction and collaborative motion, exoskeleton controllers need to accurately determine human motion intentions, adjust actuators in real-time through various advanced control strategies and efficient algorithms or models, and drive robot joints to assist the human body in completing specific work tasks.

Numerous challenges remain in collaborative control, such as improving sensing accuracy and motion intent recognition capabilities, precisely predicting and continuously tracking motion trajectories, enhancing system adaptability and active disturbance rejection, reducing latency, and increasing response bandwidth. These issues drive researchers to pursue advancements not only in actuators, transmission mechanisms, and materials but also in sensing technologies and collaborative control strategies.

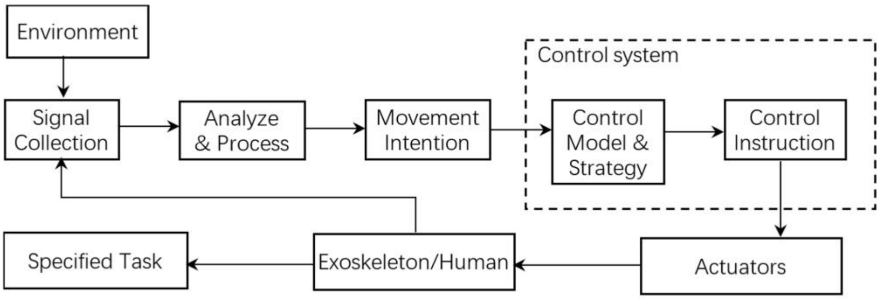


Figure 1. General Framework of Human-Machine-Environment Collaborative Control

The purpose of this comprehensive review is to assist readers in gaining a more detailed, and thorough understanding of the collaborative control technologies, methodologies, and relevant literature associated with human augmentation exoskeletons, thereby contributing to further research in this field. At the time of writing this article, several reviews on exoskeleton assistance and control strategies had already been published; however, their content was relatively outdated or primarily focused on aspects such as structural design and performance evaluation, with fewer reviews covering sensing, intent recognition, and collaborative control strategies comprehensively. For instance: Yan et al.

[26] (2015) comprehensively classified control strategies by single- and multi-joint systems. Ahmed et al. [27] (2016) analyzed online control strategies, emphasizing sensitivity amplification, autonomous control, and variable admittance control. Baud et al. [28] (2021) reviewed lower-limb exoskeleton gait control across high-, mid-, and low-level human-machine interaction layers, albeit briefly and with a rehabilitation focus. Luo et al. [29] (2024) summarized perception and control strategies for lower-limb exoskeletons but provided limited depth on control methodologies. Recent advancements in artificial intelligence (AI) and deep learning are driving innovations in control models and algorithms, promising significant performance improvements. This review focuses on collaborative control literature, systematically analyzing sensing systems, motion pattern recognition, gait trajectory planning, and control strategies.

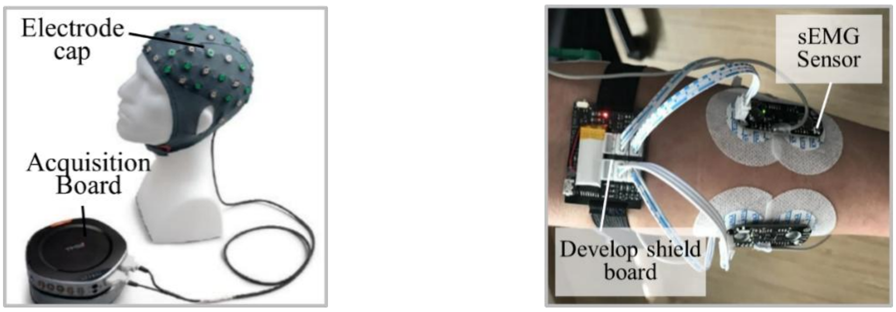
Literature collection: Using keywords "Exoskeleton," "control strategy," and "intent recognition" in Google Scholar (2015–2025), 377 articles were initially identified. Secondary filtering with "cooperative" narrowed this to 95 articles. After excluding studies on materials, mechanical design, and rehabilitation, and incorporated seminal control theories and review literature on strength-augmentation exoskeletons published around 2010, selecting 114 articles for this review. The remainder of this paper is organized as follows: Section 2 introduces the sensing detection systems, Section 3 introduces human motion intent recognition and prediction, Section 4 introduces control strategies for human-machine collaboration. The final section summarizes the current status and challenges in exoskeleton collaborative control and provides prospects for future improvements.

2. Sensing Detection Systems

The sensing and monitoring system comprises sensors, signal acquisition circuits, and a host unit responsible for multi-channel signal integration, filtering, and computational analysis. This system is critical for enabling exoskeletons to monitor human motion and make follow-up decisions. Sensors are categorized by structure (mechanical/non-mechanical) and material (flexible/rigid). Detection methods are classified as prior detection or posterior detection, depending on whether motion intent is directly embedded in the sensed information. Based on detection targets, exoskeleton sensing technologies fall into three categories: human physiological signal monitoring, kinematic/dynamic measurements, and environmental sensing.

2.1. Human Physiological Signal Monitoring

The most representative devices for human physiological signal detection are electromyography (EMG) and electroencephalography (EEG) acquisition units (Figure 2), which play a critical role in tracking muscle activity and brain signals. These systems provide preemptive information about human motion intent—detected before limb movement and unaffected by environmental factors—making them a widely researched and implemented prior detection technology in recent strength-augmentation exoskeleton applications.



(a) EEG

(b) sEMG

Figure 2. Sensors for monitoring human physiological information

EMG sensors offer multiple advantages in strength-augmentation exoskeletons, including enabling natural and intuitive control by capturing muscle activity signals. However, integrating EMG sensors increases system complexity, requiring additional hardware and software for signal processing and control. They are also susceptible to external factors such as sweat, motion artifacts, and noise, which may compromise signal quality and exoskeleton performance. Furthermore, excessive EMG sensors can cause user discomfort and raise system costs.

EEG sensors, distinct from EMG, capture broad motion intent through dense placement on the scalp and are often termed brain-computer interfaces (BCIs) with significant application potential. However, EEG signals—voltage fluctuations caused by ionic currents between neurons—suffer from low signal-to-noise ratios, poor spatial resolution, and signal attenuation through the skull. Additional artifacts from eye movements, electrocardiography (ECG), and respiration further complicate detection. EEG technology remains an emerging field with unresolved challenges for direct exoskeleton control.

Muscle stiffness sensors based on biomechanical principles have been developed for detecting muscle activity [30]. When muscles receive motor commands from the nervous system, changes in length and cross-sectional area alter stiffness. Micro-pressure sensors embedded in elastomeric sleeves can measure these changes, circumventing EMG's electrode placement issues. However, when applied to the torso, thighs, or calves, detecting subtle stiffness variations across multiple muscle groups proves less accurate and sensitive than EMG/EEG, with inherent latency. Thus, they are primarily used for auxiliary qualitative assessments.

2.2. Kinematic and Dynamic Measurements

Inertial measurement units (IMUs) measure kinematic and dynamic properties, typically integrating accelerometers, gyroscopes, and magnetometers (Figure 3b) to track exoskeleton and limb orientation, position, and motion. An IMU is an electronic device capable of measuring six degrees of freedom (6DoF): linear acceleration along three orthogonal axes and angular velocity (via triaxial gyroscopes). Its signals are processed to determine 3D spatial position and orientation. Magnetometers are included to measure gravitational forces, with each sensor collecting data for three body axes: roll, pitch, and yaw. While IMUs directly measure linear acceleration and angular velocity—yielding superior outputs compared to time-derived positional data—a key limitation is drift in positional measurements, caused by noise accumulation during signal integration, leading to gradual deviation from true values.

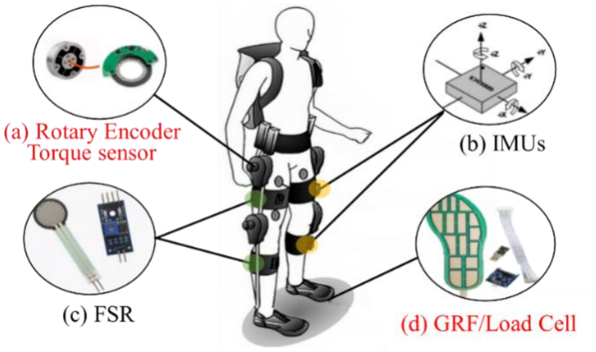


Figure 3. Sensors for Kinematics and Dynamics Measurement

Force and torque sensors, including strain gauges, capacitive, piezoelectric, and piezoresistive sensors (Figure 3a), measure forces/torques applied to joints such as the hip, knee, and elbow. These sensors provide foundational data for algorithms determining joint assistance magnitude in strength-augmentation exoskeletons, enabling precise adaptation to user intent. Continuous force/torque monitoring also detects anomalies to ensure user safety. Figure 3d illustrates ground reaction force sensors (GRF), commonly used for gait analysis in exoskeletons. Flexible thin-film strain gauge pressure sensors (FSR, Figure 3c) accurately detect minute force variations, measuring contact forces to monitor and evaluate human-machine interaction compliance. Flexible strain gauges, deployable along limbs or the waist, enable real-time force/torque measurement during walking or lifting, enhancing collaborative control.

Displacement sensors are critical in lower-limb exoskeletons for precise linear or angular displacement measurement during motion. These sensors (Figure 3a), including laser displacement, linear, and angular sensors/encoders, improve system accuracy and control precision in rehabilitation exoskeletons. Strain gauges, inductive sensors, and Hall effect sensors are used for small displacements, while optical and magnetic grating technologies measure larger displacements. A key drawback is their high power consumption, though recent advances in mechanical and self-powered displacement sensors show promise for exoskeleton integration.

2.3. Environmental Perception

Environmental sensing enhances exoskeleton functionality. As shown in Figure 4, sensors such as ultrasonic, infrared, and LiDAR are integrated into lower-limb exoskeletons for terrain and obstacle detection, enabling rapid gait mode switching and collision avoidance, particularly in rehabilitation systems. These sensors improve safety and adaptability in diverse environments.

(a) Ultrasound transducer (b) IR Sensor (c) Laser Lidar

Figure 4. Sensors for Enviororment Detecting

Based on different exoskeleton application requirements, some studies have introduced more types of sensing technologies for environmental perception. For instance, visual sensing detection [31] utilizes 3D cameras to detect the surrounding terrain, enabling obstacle avoidance or navigation. Speech recognition [32] employs sound sensors in conjunction with speech recognition technology to provide data for precise control commands and coordination of the exoskeleton. Tactile sensing detection [33] detects touch, pressure, or vibration, and can be embedded in the area where the exoskeleton interacts with the user's body, providing feedback on fit and comfort. Temperature sensing detection [34] ensures that the exoskeleton's motors, batteries, or other components do not overheat during operation.

3. Human Motion Intent Recognition and Prediction

Human motion intent recognition is the foundation and prerequisite for human-machine collaborative control. The definition of human motion intent varies across scenarios. The most direct intent originates from the wearer’s brain [35], which can serve as a trigger for initiating robotic motion. More commonly, human motion intent is simplified into predefined action sets [36] or short-term motion trajectories (velocity or displacement), referred to as motion patterns or gaits. While displacement and velocity provide trajectory information about human motion, the emergence of force often accompanies changes in trajectory and motion patterns. Yan et al. [26] regard human joint forces/torques and human-machine interaction forces as the most universal motion intent in exoskeleton systems. While various strength-augmentation exoskeletons differ in structure and purpose, they all detect human information through the aforementioned sensing methods, extract data features, and classify motion intent using algorithms. In addition to recognition, accurate prediction and estimation of future motion trajectories and gaits are required to closely follow human movement and provide timely force or torque assistance.

3.1. Motion Pattern and Gait Phase Recognition

Motion patterns primarily refer to terrain- or task-related motion states, such as level walking, stair ascent/descent, and load carrying. Automatic, smooth, and rapid switching of motion patterns is a critical research goal for human-exoskeleton collaboration, enabling natural gait following and improved wearability. Motion pattern identification and switching can be classified based on signal sources, currently including bioelectrical signal-based classification (EMG, EEG) and kinematic signal-based classification (joint kinematics/dynamics).

Gait phase recognition further refines the human-machine interaction process by detecting periodic, task-specific sub-phases (e.g., stance, swing) within motion patterns like walking or stair climbing. Different gait phases often employ distinct control strategies—e.g., inverted pendulum models for swing phases versus dual-support models for stance phases. Accurate gait phase recognition is essential for real-time, natural joint actuation.

Gait detection primarily relies on plantar sensing and limb sensing technologies. Plantar sensing identifies gait phases by measuring human-machine interaction forces or ground reaction forces. For example, XOS and BLEEX use torque sensors installed on the feet to capture interaction forces/torques and analyze gait phases. BLEEX can recognize three gait phases: double-leg stance, left-leg stance, and right-leg stance. HULC employs flexible piezoresistive (FSR) sensors in pressure-sensitive insoles to detect forces and distinguish between swing and stance phases. The MIT Exoskeleton and HAL-5 combine ground reaction force (GRF) sensors with tilt sensors for gait phase identification. Limb sensing utilizes IMUs or angle sensors to detect limb/trunk postures. For instance, ReWalk, eLEGs, and X1 use torso-mounted angle sensors to identify swing phases during walking, combined with plantar pressure sensing for stance phase determination.

Another approach leverages physiological signals with prior advantages for gait phase recognition. HAL and PAS detect muscle activity via sEMG sensors on the thighs and calves to distinguish between stance and swing phases. MindWalker employs EEG-based brain-computer interfaces (BCIs) [37], dividing gait into nine phases: double-leg stance, weight shift to left leg, right-leg half-swing, right-leg full-swing, double-leg stance with left-leg preparation, weight shift to right leg, left-leg half-swing, left-leg full-swing, and double-leg stance with right-leg preparation.

Multi-sensor fusion and machine learning techniques are widely used in gait pattern recognition to enhance system performance and robustness [38-43]. As discussed in Section 2, single-sensor approaches (e.g., kinematic or physiological sensing) are prone to interference or missed detection. For example, sEMG and EEG are susceptible to physiological artifacts, while plantar pressure sensing fails during swing phases or on uneven terrain. Soft Exosuit integrates force sensors, gyroscopes, and IMUs to jointly estimate joint angle changes for gait recognition. Huang et al. [44] combined EMG signals and GRF data as inputs for a support vector machine (SVM)-based classifier, achieving 99% accuracy for stance phases and 95% for swing phases. Young et al. [45] proposed fusing EMG and IMU signals with dynamic Bayesian networks to recognize basic gait patterns (e.g., level walking, stair ascent/descent, slope walking), reducing transition and steady-state errors.

3.2. Gait Prediction

Exoskeletons are typical human-machine coupled systems with humans in the inner loop. To achieve the function of assisting the human body, predicting human motion is an unavoidable key issue. This requires the perception system to measure human-machine interaction information and then predict human motion based on this information. Currently, widely used gait prediction information still includes human biomechanical signals and human-machine physical interaction signals (contact forces, poses, etc.). Gait or trajectory prediction methods are mainly divided into three categories: predefined trajectory prediction based on finite state machines, model-based prediction, and continuous prediction dominated by intelligent algorithms such as machine learning.

Early assistive exoskeletons primarily predicted gait trajectories based on predefined trajectory triggering. Predefined trajectory prediction identifies potential predefined gait phases by detecting human biological signals or human-machine interaction signals, sets up finite state machines, and performs gait prediction and switching actions according to preset motion trajectories. For example, ReWalk [15] uses wrist pads to measure the interaction force between the human body and the exoskeleton to trigger the control system to estimate the next motion gait based on predefined trajectories such as standing, sitting, or starting to walk. Torso tilt sensors are used to trigger gait switching. Exoskeletons such as eLEGs [46], LOPES [47-48], and MindWalker [49] also adopt this predefined gait prediction method. This prediction is discrete-time prediction of human motion, incapable of continuous action prediction, which constrains natural human movement and deprives the human body of autonomous motion. Once such prediction errors occur, the irreversibility of predefined trajectories may cause harm to the human body.

Model-based prediction using dynamics models or human musculoskeletal models is also widely employed. By obtaining human-machine interaction or human biological information through interactive detection as inputs to exoskeleton dynamics or musculoskeletal models, real-time gait is estimated through computation. BLEEX [50] established an inverse kinematics model coupling the exoskeleton and human body, enabling rapid tracking and prediction of human limb motion gait by adjusting sensitivity amplification coefficients. PAS [51] triggers assistance by measuring human-machine interaction forces via muscle stiffness sensors and calculates the required assistive torque using a simplified static model with whole-body joint angles as variables. HAL [52] triggers joint assistance through sEMG signal intensity, with assistive torque calculated via a mathematical model combining S-curve torque, viscous torque, and human-machine gravity compensation torque. BE [53] predicts motion trajectory outputs using a unilateral upper and lower limb second-order dynamics model established based on detected human-machine interaction forces. Ai et al. [54] proposed an EMG data-driven musculoskeletal model based on the Hill muscle model, combined with a musculoskeletal geometric model, to estimate the wearer's joint torque and predict the assistive compensation for exoskeleton joint actuators. Wu AR et al. [55] proposed a biologically inspired neuromuscular controller (NMC) using a lower-limb muscle dynamics model, which generates motion trajectories for different speeds and terrains by inputting joint angles, stance, and swing information. Di et al. [56] developed both an EMG-driven Hill-type neuromuscular model (HNM) and a linear proportional model (LPM) for ankle exoskeletons to estimate ankle torque, concluding that HNM is more accurate and produces smoother motion.

The accuracy of model-based prediction heavily depends on the precision of the established mathematical or biomechanical models. Due to the complex physical characteristics of human limbs and exoskeleton systems, many studies simplify joint or external conditions in their dynamics models, significantly reducing prediction accuracy. This makes it difficult to clearly and accurately determine the relationship between human-machine interaction information and human motion gait. Although human motion gait is a nonlinear function of human-machine interaction information and cannot be obtained through mathematical modeling, machine learning methods can approximate it. Yanan Li et al. [57] estimated unknown human motion trajectories using online RBFNN with human-machine interaction forces as inputs. Tran et al. [58] proposed using Gaussian Process Regression (GPR) for supervised learning to map the relationship between human-machine interaction forces and exoskeleton joint kinematic factors.

In recent years, with deeper research on gait prediction, more measurement information reflecting human motion intent—including the aforementioned plantar pressure, human-machine interaction forces, bioelectrical signals, forces, and human motion postures—has been used in gait prediction and generation through single or multi-sensor fusion combined with machine learning and deep learning techniques, achieving significant progress [59-67]. Zebin et al. [68] proposed predicting six limb activity angle trajectories using IMU data sequences and an LSTM deep recurrent neural network algorithm, achieving an average accuracy of 92%. Ma et al. [69] utilized long short-term memory (LSTM) with root mean square (RMS) features and time-advanced sEMG features to estimate knee angles, obtaining smaller root mean square errors (RMSE). Harib et al. [70] performed kinematic modeling via virtual constraints and generated single-cycle gait trajectories using offline trajectory optimization combined with machine learning. Qin et al. [71] proposed a prediction algorithm based on least squares support vector regression (LS-SVR) to predict the next moment's gait data for human lower limbs. Cheng Hong et al. [72] dynamically adjusted Dynamic Movement Primitive (DMP) oscillator parameters using machine learning to enable the human-machine coupled system to adapt to current terrain and motion gait predictions. Zhou et al. [73] proposed a gait trajectory planning algorithm based on kernelized movement primitives (KMP), adjusting shape parameters online to ensure similarity between predicted and reference trajectories. Wu et al. [74] established a personalized gait pattern prediction model using Gaussian process regression with automatic relevance determination to map relationships between body parameters and gait characteristics under different walking speeds.

In summary, model-based gait prediction methods do not require complex sensing systems, but improving model accuracy remains their primary challenge. Future research directions for exoskeleton gait prediction and generation will involve intelligent optimization methods that collect and analyze gait data, mine individual user preferences to generate gaits offline, and combine adaptive methods to adjust gait parameters online, constructing a closed-loop human-machine interaction acquisition system.

4. Collaborative Control Strategies

Exoskeletons are strongly coupled human-machine systems, where coordinated control is the most critical issue in their development, directly affecting performance and user experience. After the exoskeleton system acquires human motion intent, appropriate control strategies must be designed to drive the exoskeleton to follow human motion quickly and accurately, achieving human-machine coordination for smooth, compliant motion and ensuring human comfort. The ideal human-machine integration state is when the exoskeleton provides assistance without interfering with normal human movement, making the wearer almost unaware of the exoskeleton's presence. Current objectives for human-machine collaborative control focus on finding superior control strategies, manifested in three aspects: minimizing human-machine interaction forces for compliant experience, synchronizing gait timing and speed for precision, and improving motion trajectory accuracy with dynamic parameter adjustability.

Baud et al. [75] categorized exoskeleton control strategies into three levels from a hierarchical control perspective: high-level, mid-level, and low-level control. High-level control is responsible for task mode selection, mid-level control detects gait phases and states, and low-level control executes joint position or torque control. Most exoskeleton systems combine controls across multiple levels. This paper references hierarchical control classification and introduces strategies based on collaborative control objectives and targets, categorized into gait trajectory control, force information control, motion pattern adaptation, and intelligent control.

4.1. Gait Trajectory Tracking Control

Among the numerous control strategies for strength-augmentation exoskeletons, one of the simplest methods is trajectory tracking, which involves replaying predefined position or velocity curves on actuators. As shown in Figure 5, this approach typically comprises three components: offline trajectory definition, online trajectory adjustment, and real-time trajectory tracking. Offline trajectory definition can be fine-tuned using normal human motion trajectory datasets from CGA (Computerized Gait Analysis) or generated from pre-collected data tailored to the wearer's individual characteristics, including factors such as center-of-mass balance. Online trajectory adjustment typically includes safety zone detection (e.g., safe joint angles/positions) and selects optimal trajectories and parameters adapted to real-world walking scenarios via finite state machines (FSMs) configured based on motion intent or triggering conditions. For real-time trajectory tracking, classical PID control is a common choice and is often embedded in motor drives. Other trajectory-based control strategies include sliding mode control [76], LQR control [77], and model-based control methods with disturbance rejection [78]. To date, trajectory tracking control has been adopted by many commercial exoskeletons, such as HAL [52], ReWalk [15], Ekso [18], and HongDa SMA [79].

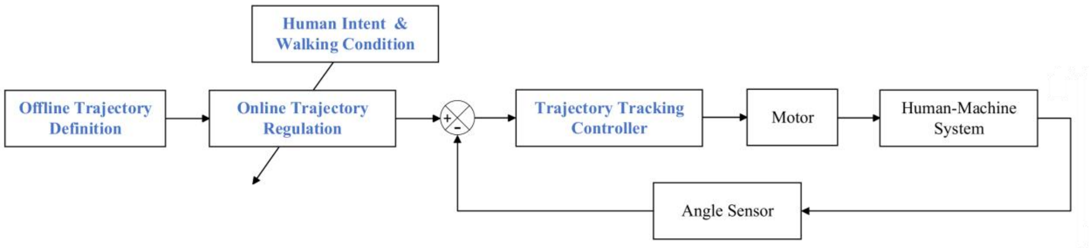


Figure 5. General framework of trajectory tracking control

4.2. Force Information-Based Control

Force information-based collaborative control focuses on the contact forces between the wearer and the exoskeleton. This class of control methods requires detecting human-machine interaction forces. Commonly used strategies include admittance shaping control, force/position hybrid control, sensitivity amplification control, zero moment point (ZMP) control, and ground reaction force (GRF) control.

4.2.1. Admittance Shaping Control

Admittance shaping control is widely applied in robot-environment (human or physical) interaction. It optimizes robot compliance, stability, and adaptability by adjusting admittance model parameters (e.g., stiffness, damping, inertia) based on interaction torques. Admittance shaping encompasses two approaches: admittance control and impedance control. Admittance control treats external forces as inputs to a virtual admittance model, outputting desired joint motions (position, velocity, or acceleration). Impedance control uses the error between joint and human motion as input, applying an impedance model to output joint torque for trajectory tracking. The former suits active compliance requirements, while the latter is ideal for precise force control tasks. Figure 6 illustrates the admittance shaping control framework based on these two models [80].

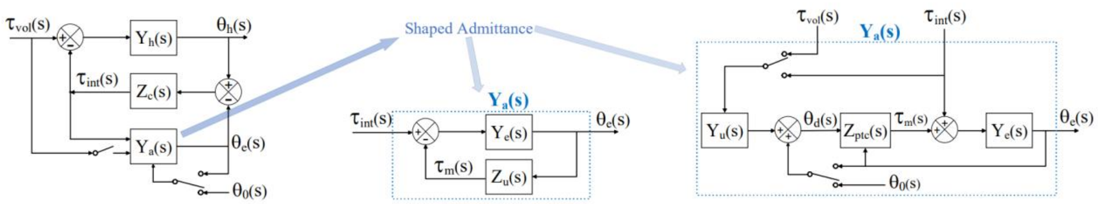


Figure 6. Framework of admittance shaping. (a) Human-machine system; (b) Exoskeleton with impedance controller; (c) Exoskeleton with admittance controller.

Aguirre-Ollinger et al. [81] proposed an active impedance control method to enable the exoskeleton robot to output negative damping, compensating for the inertia of the coupled system formed by the wearer's lower limbs and the exoskeleton. Nagarajan et al. [82] introduced an Integral Admittance Shaping Control (IA) method for controlling Honda's Walking Management Assist Exoskeleton (WHA).

4.2.2. Force/Position Hybrid Control

Force/position hybrid control refers to separately controlling the robot's force and position to achieve desired position and force outputs. This method combines closed-loop position control and force control. As shown in Figure 7, the general framework involves input signals derived from deviations between actual and desired force/position values. These signals are mapped to joint controllers via coordinate transformations, with the sum of force and position control outputs forming the total joint control command, thereby achieving the exoskeleton's desired motion control.

The Swiss Lokomat lower-limb rehabilitation exoskeleton [83] employs a force/position hybrid adaptive control strategy in its active training mode, building on gait planning control, and has validated the effectiveness of these methods. The U.S. ALEX active lower-limb exoskeleton [84] applies a force/position hybrid control algorithm in its active training mode, enabling the exoskeleton to exert appropriate forces on the wearer's legs for desired gait planning. Anderson et al. proposed combining force/position hybrid control with impedance control to effectively suppress system oscillations caused by control mode switching [85]. However, such control relies on accurate modeling of exoskeleton-human dynamics, demanding high computational real-time performance. Additionally, real-time monitoring of force and position changes is required during implementation.

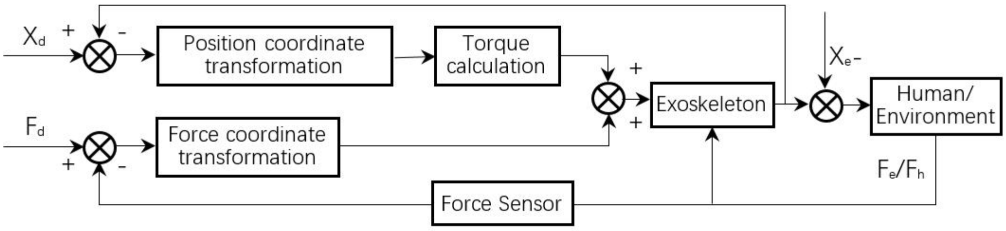


Figure 7. Hybrid force/position control schematic diagram

4.2.3. Sensitivity Amplification Control

The sensitivity amplification control strategy defines the transfer function from the forces applied by the wearer to the exoskeleton's output as the sensitivity function, with the goal of maximizing this function through controller design to enable small forces to alter the exoskeleton's motion. However, this strategy strictly depends on the accuracy of the exoskeleton's inverse dynamics model [50]. U.S. military exoskeletons such as BLEEX, HULC, and XOS have adopted this control strategy. Among these, BLEEX first proposed this strategy and established inverse dynamics models for three gait phases: single-leg stance (seven-link dynamics model), double-leg stance (three-link dynamics model for each leg), and one-leg stance with a redundant leg (three-link model for the stance leg and four-link model for the redundant leg). Gait phases are determined via plantar pressure sensors. The SAC control strategy requires no sensors between the human and machine, controlling the exoskeleton's motion by amplifying sensitivity to forces or torques, achieving minimal interaction forces and high compliance. However, it responds to involuntary human movements or external disturbances, risking system instability and requiring active balance maintenance by the user. Song et al. [86] proposed a Model-based Interaction Prediction (MIP) strategy based on SAC, amplifying both predicted interaction forces and wearer-applied forces to correct trajectory errors and reduce reliance on precise dynamics models. Zheng et al. [87] integrated SAC with Deep Reinforcement Learning (DRL) to decrease model dependency and adapt to dynamic human-exoskeleton interaction (HEI) dynamics.

4.2.4. Ground Reaction Force (GRF) and Zero Moment Point (ZMP) Control

ZMP control, a traditional robotic method for maintaining balance and stability, is also critical for human-exoskeleton collaboration. This strategy has been applied in exoskeletons such as the lower-limb exoskeleton robot at Nanyang Technological University, Singapore [88], HAL, and BLEEX. The ZMP stability criterion defines the horizontal component of the resultant moment from inertial and gravitational forces as zero, termed the ZMP. If the ZMP lies within the polygon formed by the robot's foot-ground contact, the system remains stable. As shown in Figure 8 [89], in ZMP-based exoskeleton control, the human ZMP is obtained via plantar GRF measurements or IMU data using ZMP calculation algorithms; The exoskeleton's ZMP is derived from joint encoder angles through kinematic models and pose-based ZMP algorithms. The deviation between these ZMPs is fed into the control system as external feedback. After ZMP compensation, corrected gait trajectories are synthesized via inverse kinematics and desired gait profiles, tracked by internal controllers. Wang et al. [90] utilized ZMP theory and cubic spline interpolation to generate stable, smooth gaits for human-exoskeleton coupled systems. Jatsun et al. [91] employed the Iterative Linear Quadratic Regulator (ILQR) as a feedback controller based on ZMP control to maintain balance during sagittal-plane sit-to-stand transitions.

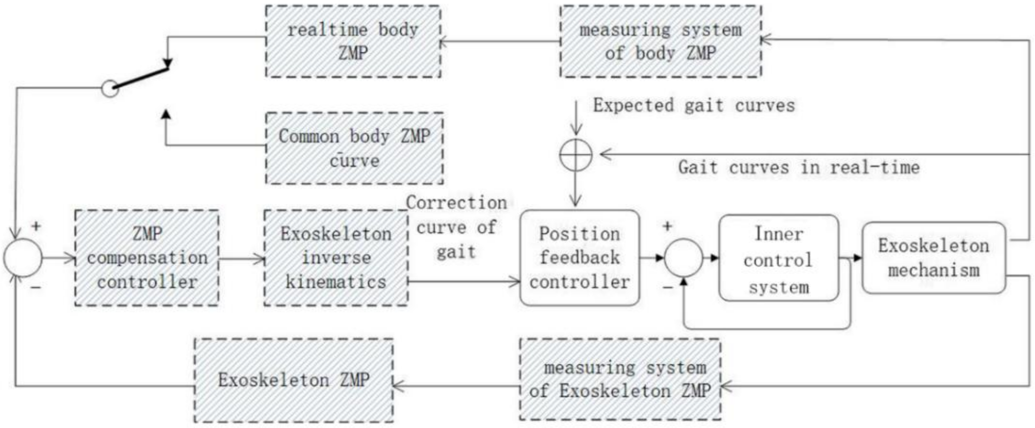


Figure 8. ZMP & GRF based control schematic diagram [89]

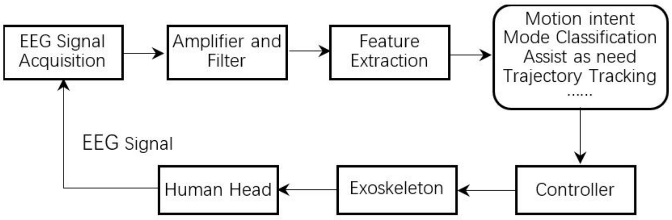
ZMP-based control requires the ZMP to remain within the stability region, demanding accurate mathematical models and computationally intensive calculations. Alternative strategies directly map GRF pressure curves to human motion trajectories but suffer from noise, artifacts, and latency, necessitating further optimization.

4.3. Bioelectrical Signal-Based Control

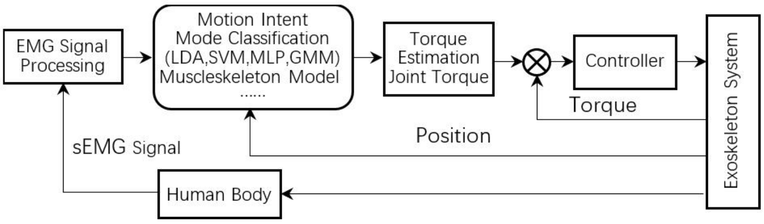
Bioelectrical signal-based control is a high-level strategy that primarily achieves motion task mode selection and movement planning through direct recognition of motion intent. Currently, the most commonly used detection signals are surface electromyography (sEMG) (muscle force) and electroencephalography (EEG). Through feature extraction and intent decoding, motion pattern recognition and subsequent low-level position/torque control are accomplished.

The principle of EEG-based control is shown in Figure 9(a). It requires establishing a brain-machine interface (BMI) to amplify and filter extremely weak EEG signals (below 100 μV), extract features, recognize motion intent via pattern classification, and then connect to conventional control strategies such as trajectory tracking or on-demand assistance. Miguel Nicolelis [92] successfully enabled a paraplegic user wearing an EEG-controlled exoskeleton to stand from a wheelchair, take steps, and kick a soccer ball. Edelman et al. [93] utilized EEG source imaging (ESI) technology to achieve precise classification of four wrist movements: internal rotation, external rotation, extension, and flexion. Like EEG signals, sEMG signals have prior advantages, greatly avoiding electromechanical delays, and are commonly used for motion intent detection in limb musculoskeletal systems.

The principle of sEMG-based control is shown in Figure 9(b). The sEMG signals detected from limbs or the torso undergo preprocessing and feature extraction to obtain motion intent. Combined with simple proportional amplification, musculoskeletal models, or nonlinear machine learning methods, motion trajectories and joint torques are estimated to drive the exoskeleton in completing tasks. Using sEMG sensors requires no complex operations—signals are acquired via electrodes attached to the skin, offering convenience and efficiency. Targeted monitoring of specific muscle groups has gained increasing favor among exoskeleton researchers, with continuous breakthroughs in motion intent recognition rates through novel classification algorithms. He et al. [94] proposed an LSTM-Adaptive Robust Iterative Learning Control (LSTM-ARILC) framework based on sEMG for human-exoskeleton collaboration in variable walking environments, achieving 99% accuracy in continuous motion estimation and adaptive tracking control. In recent studies, Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), K-Nearest Neighbor (KNN), Decision Tree (DT), Random Forest (RF), Hidden Markov Model (HMM), Bayesian Classifier (BC), Fuzzy Control (FC), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Artificial Neural Network (ANN) along with their improved variants have been applied to sEMG recognition [95].



(a) Principles of EEG Signal Control



(b) Principles of sEMG Signal Control

Figure 9. Control schematic based on bioelectric signals

Due to the limitations of EMG signals, such as cross-talk between adjacent muscles, high noise, difficulty in precise detection, and unsuitability for certain users (e.g., spinal cord injury patients), researchers have combined sEMG and EEG control to improve applicability and accuracy. Li et al. [96] proposed a multimodal fusion human-machine interface integrating sEMG and motor imagery EEG for lower-limb exoskeleton motion intent recognition, achieving an average recognition rate of 89.5%. Yang et al. [97] developed a low-cost, portable wrist exoskeleton based on EEG-sEMG joint recognition, using only 3 EEG channels and 8 sEMG channels, achieving recognition rates of 80.12% and 94.49% for 2-class and 6-class motion intents, respectively. However, compared to traditional control techniques based on mechanical or muscular activity, the reliability and stability of single-modality EEG or sEMG control for gait intent recognition remain inadequately validated, with overall lower performance. Multimodal fusion and algorithm optimization are key future directions for such methods.

4.4. Intelligent Control

Exoskeletons are highly coupled human-machine systems with inherent nonlinearity, joint nonlinearities, electromechanical delays, and uncertainties such as sensor noise and external disturbances (e.g., motor vibration, device weight, human tremors, sweat/rain, impacts). These factors make precise kinematic or muscular modeling challenging. Most exoskeleton control strategies rely on simplified or linearized "gray-box" models with nonlinear components, limiting human-machine synergy. Intelligent control algorithms, which treat the system as a "black box" without requiring mathematical models, are seen as effective solutions. These strategies leverage prior knowledge or predefined rules—e.g., neural networks embedding system information in their architecture, or fuzzy systems governed by behavioral rules. Common approaches include fuzzy control, neural network control, expert systems, learning control, and intelligent search algorithms (genetic algorithms, particle swarm optimization, differential evolution). Fuzzy and neural network controls are the most representative.

For exoskeletons, these methods are useful for estimating continuous state parameters (e.g., joint angles and torques during motion). However, continuous monitoring can be computationally intensive, demanding high data storage and processing. Sun et al. [98] addressed uncertain nonlinearities in exoskeleton MIMO systems by proposing a simplified adaptive fuzzy system with compensation terms, reducing chattering and improving performance over traditional methods. Han et al. [99] combined time delay estimation (TDE) with computed torque control (CTC) to estimate unmodeled dynamics and disturbances, designing an adaptive RBF neural network to compensate for TDE errors, demonstrating significant improvements. Kang et al. [100] developed a sensor fusion-based neural network for real-time hip exoskeleton gait phase estimation, avoiding traditional stride-averaged labeling and enhancing collaboration.

To further improve robustness and prediction, researchers increasingly integrate traditional methods (PID, adaptive, optimal control) with intelligent algorithms for nonlinear system estimation. Yang et al. [101] proposed a fuzzy optimal gain-based adaptive robust control, theoretically proving optimal gain existence and validating it on a 2DOF lower-limb exoskeleton. Foroutannia et al. [102] designed an adaptive fuzzy impedance controller (AFIC) combined with a CNN (Figure 10), where CNN inputs (EMG, IMU, FSR, angle signals) guide AFIC to successfully estimate joint torques under walking speed uncertainties. Lin et al. [103] implemented a pneumatic lower-limb exoskeleton using ANN-PID hybrid control (Figure 11), featuring a dual-layer ANN for predicting pneumatic muscle (PAM) pressure differences and PID compensation commands, optimized via particle swarm optimization (PSO) to bypass complex modeling while compensating for PAM nonlinearities.

In recent years, deep learning and reinforcement learning algorithms have also been increasingly used to control the motion of lower-limb exoskeletons, forming a hotspot of scholarly attention [104-109]. Zheng et al. [110] developed an end-to-end deep reinforcement learning framework for lower-limb exoskeleton control. As shown in Figure 12, the control framework has two levels: the high-level uses a deep reinforcement learning algorithm to predict human motion intent from exoskeleton signals and human-exoskeleton interaction (HEI) force signals, while the low-level uses a proportional-derivative (PD) controller to track human motion. This control framework, based on deep neural networks, can directly estimate human motion intent without requiring kinematic or dynamic models of the exoskeleton system.

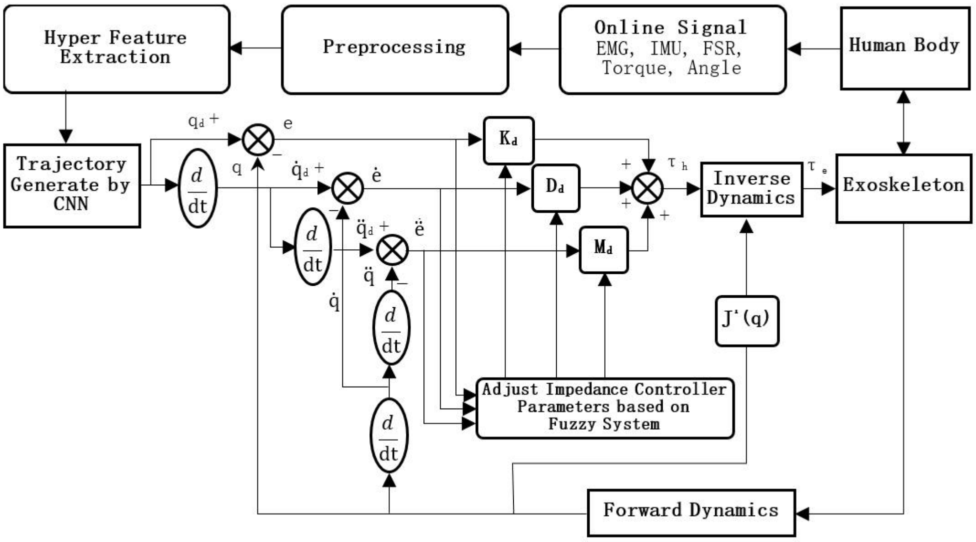


Figure 10. AFIC Combined with CNN [102]

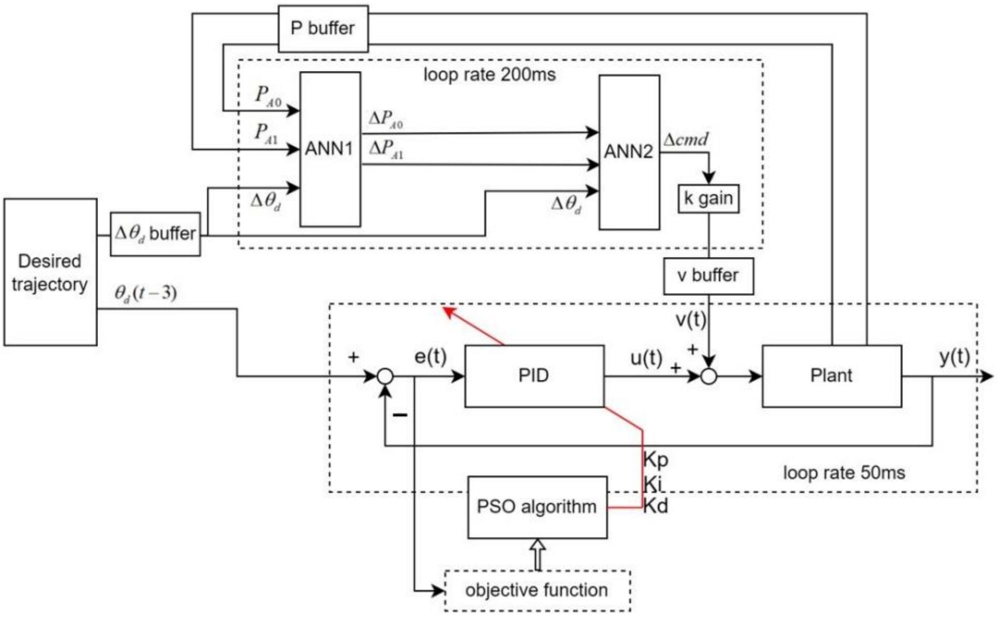


Figure 11. PSO tuned PID with ANN controller.[103]

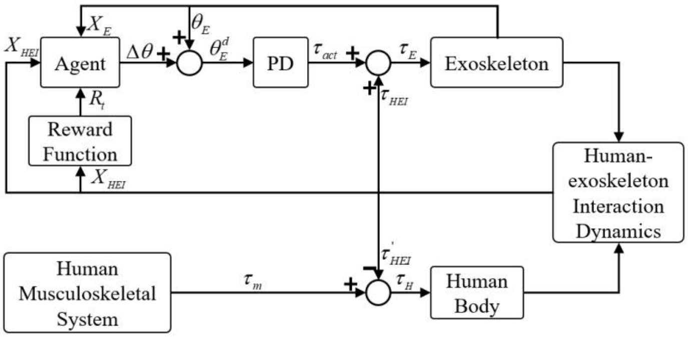


Figure 12. Diagram for E2EDRL [110]

Huang et al. [111] proposed a hierarchical interactive learning (HIL) control strategy based on gait phase and motion pattern recognition. As shown in Figure 13, this strategy consists of high-level learning and low-level control. The high-level learning identifies gait phases and motion patterns, utilizing Dynamic Movement Primitives (DMP) to segmentally learn desired joint torque profiles. The low-level control employs the learned DMPs to output torque according to gait phases and motion patterns, while using reinforcement learning to dynamically adjust DMP control parameters in real time to minimize human-exoskeleton interaction forces.

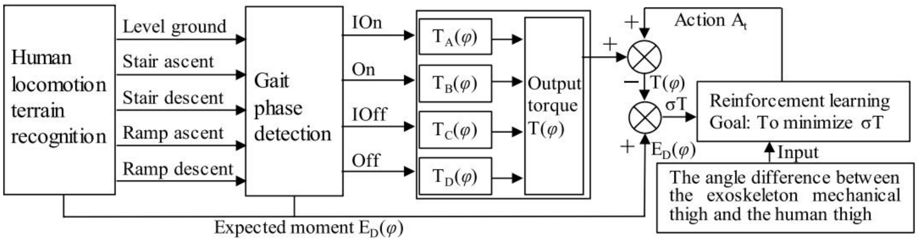


Figure 13. Hierarchical Interactive Learning (HIL) control strategy based on gait phase and motion pattern recognition [111]

Zheng et al. [87] proposed a strategy called Sensitivity Amplification with Deep Reinforcement Learning (SADRL), which builds on the sensitivity amplification control (SAC) strategy. This approach uses deep reinforcement learning with exoskeleton posture parameters to search for optimal sensitivity coefficients S enhancing the control compliance of lower-limb exoskeletons. The reinforcement learning training process is implemented through a simulated environment. Experimental results demonstrated that SADRL significantly reduces human-exoskeleton interaction forces to 0.54 times those of the original model.

These model-free intelligent methods, while promising, involve computationally intensive training processes, significant time and resource demands, and high hardware requirements for exoskeletons, posing challenges to portability and energy efficiency. To address this, Wu et al. [112] proposed a Graph Convolutional Network Model (GCNM) for gait phase classification in lower-limb exoskeleton control. Experiments demonstrated that GCNM achieves significantly improved prediction accuracy (maximum 97.43%) and robustness for gait phase classification across level ground, uphill, and downhill environments, with a labeling rate below 10%. GCNM exhibits unparalleled adaptability to diverse environmental conditions. Lee et al. [113] employed a Deep Convolutional Network (DCNN) with three 1D convolutional layers and two fully connected layers for real-time user-independent slope prediction, achieving an average RMSE of 1.5° during treadmill and overground walking. This approach mitigates noise and sensor drift during motion, enhancing adaptability across users and terrains.

Reinforcement learning can also be model-based, offering higher efficiency than model-free methods but remaining computationally intensive. Model-based algorithms explicitly construct a transition dynamics model of the system, simulate and predict system behavior internally, and derive optimal policies through evaluation and refinement. Li et al. [114] proposed a learning-based variable impedance control method using model-based reinforcement learning to learn optimal impedance adjustment policies. A Gaussian process model serves as the system's transition dynamics model, with experimental results showing the method's efficiency in learning force control tasks with minimal interactions.

Fuzzy control requires no precise mathematical models, enabling real-time handling of nonlinear complex systems and adaptive control of robots through intelligent parameter adjustments. Neural network control can approximate any complex nonlinear relationship and learn dynamic characteristics of highly uncertain systems, representing a quintessential intelligent control strategy. However, the selection of membership functions and layer weights lacks theoretical guidance, often relying on designer experience. Deep learning and reinforcement learning controllers excel in handling complex dynamic environments and human-machine interaction data, offering strong adaptability and application potential.

5. Conclusion

This paper comprehensively reviews advancements in human-environment perception, motion intent recognition, trajectory generation, and control strategies for load-bearing and mobility-assist exoskeletons. Table 1 lists representative studies from the past two decades, with a focus on intelligent control research in the last five years. Due to structural, functional, and application diversity among exoskeletons, we refrain from comparative performance evaluations but critically analyze methodological strengths and future prospects.

Table 1. Typical examples of assistive exoskeleton perception, intent recognition, trajectory tracking, and control strategies in the past 20 years

Exoskeleton or Authors, Year	Detecting Perception Sensor	Intention Recognition or Trajectory Generation Method	Control Strategy	WhetherModel-Based
BLEEX/ XOS2/ HULC [4-7], 2005/2010	IMU, PPS, Motor Encoder	Use PPS and exoskeleton posture information to determine support and swing phase gaits and track motion.	Position Control, SAC, ZMP Control	3/4-Link Mechanisms Model
MIT-Exoskeleton [8], 2006	Angle Sensors, FSR Sensors, GRF Sensors	Detect joint angles, ground reaction forces, and human-machine interaction forces to determine gait. Assist the hip with fixed force profile	Gait Trajectory Tracking Control (Triggered by FMS, Predefined Trajectories)	Hip Joint SEA Modeland Knee Joint 2-Link Model
LOPES [47], 2007	EMG, Interaction Force Sensors	Map human-machine interaction forces to predict gait; EMG is only used for evaluation.	Predefined Gait Control; Impedance Control	None, Physical Parameter Control
eLEGs [46], 2010	IMU, PPS	Cane pressure and arm IMU sensors determine swing phase gait, while plantar pressure determines stance phase gait.	Predefined Gait Control	None,Physical Parameter Control
Soft Exosuit [9],2013	IMU, Tension sensor	Use posture information from the human body and tension information at the Bowden cable's end to determine motion intent.	Position Control (Stepwise Adaptive Online Adjustment of the Motor Parameters)	None,Physical Parameter Control
NASA X1 [23], 2013	IMU, FSR	Use torso AS to determine the human body's swing phase; PPS determine the stance phase.	Force/ Position Hybrid Control; Impedance Control	Lower-Limb 3-Link Dynamics and Kinematics Model
ALEX III [84], 2013	Interaction Force Sensors, Load Cells, Torque Sensors	Desired joint torque calculated by impedance controller; Applied torques calculated by canceling human interaction force, friction, and gravity	Force/ Torque/ Impedance/ PID Control	4-Link Kinematics Model
Body Extender [53],2014	6D FSR	Use swing phase interaction force information to obtain desired angular acceleration, four gait phases are defined.	Force/ Torque Control	Human-Machine-Environment Kinetic Model
HAL-5[52], 2015	sEMG, GRF, IMU	Use sEMG information to determine motion intent, and by using GRF and IMU information to adjust	Gait Trajectory Tracking Control; Impedance	HMC Multi-Link Kinetic Model, Hill type Muscle

		motion trajectories.	Control; ZMP Control	Model
ReWalk6/Ekso [14-15][18], 2013/2015	Tile Sensor, FSR	Use the function selector on the forearm and the tilt sensor on the torso, set a threshold to trigger pre-defined motion profile	Predefined Gait Control	None,Physical Parameter Control
MindWalker [19-20], 2015	EEG, IMU	Determine the transformation of 9 walking gaits through BCI	Predefined Gait Control, Impedance Control, Bioelectric signal control(EEG)	None, Physical Parameter Control
Kyuhwa Lee, et al.[31],2016	EEG, 3D camera, Ultrasonic sensor	The BCI determines three actions: left, right, and forward movement; 3D vision and ultrasonic detection for obstacle avoidance	Predefined Gait Control, Bioelectric signal control(EEG)	None, Physical Parameter Control
Wu AR, et al.[55], 2017	IMU, EMG	By detecting human joint angles and velocities, virtual muscle torque is generated; EMG is only used for evaluation.	Force/Torque Control(NMM feedback control)	Neuromuscular model
Honda HWA [82], 2018	IMU, FSR, Tile Sensor	Use joint angle information to determine load-bearing capacity and motion posture; Use PPS information to determine walking gait.	Admittance Shaping Control	Single joint dynamics Model
LI Chao, et al. [114], 2019	Interaction Force Sensors	Use a Gaussian process model as the system's converted dynamics model, predicting uncertain states in a Bayesian manner.	Intelligent Control (RL-Based Variable Impedance Control)	Converted dynamics model from ML
HUALEX exoskeleton, Song et al. [86], 2020	IMU, PPS	Use a incremental learning module to imitate and learn the motion trajectory demonstrated manually	Force/Torque Control;Improved SAC	2-link mechanism for swinging leg, 3-link mechanism for Standing leg
Lee et al. [113],2021	IMU	Use DCNN to Predicting Slope of Moving Terrain	Intelligent Control (DCNN)	None
Wu et al. [112], 2022	FSR, Tile Sensor	GCNM recognizes four gaits between feet and ground	Intelligent Control (GCNM)	None
Zheng et al. [87], 2023	IMU, Load Cell	Use IMU information as input for CNN, output the sensitivity coefficient S for prediction optimization	Intelligent Control (SAC, DL)	Human machine coupling dynamics model
Ali Foroutanniaet al. [102], 2023	sEMG, IMU, FSR, Tile Sensor	Use CNN to estimate human intent; AFIC to control exoskeleton torque	Intelligent Control (NNC, AFIC)	None
Wenju Li et al. [96], 2024	IMU, EEG	Fusion of sEMG and EEG information, recognizing intention by end-to-end DL	Intelligent control (No specific information)	None
Qing Guo et al. [43], 2024	Encoders,3-D force sensors	Multi source information fusion, using DL regressors to obtain parameters of Lagrangian dynamics model, predicting and tracking 2DOF joint motion	Intelligent control (DeLaN Model)	Parameterized 2-Link Lagrangian Dynamics Model
ALEXO exoskeleton, J. C. Arceo et al. [41], 2024	FSR, IMU, FMG	Combine FMG and IMU signals with ANN to estimate the hip and knee joint angles of the wearer	Intelligent Control (ANN Control)	None
Huang et al. [111], 2025	IMU	Use DMP to segment and learn the required joint torque curve; Low level control output torque	Intelligent Control (Adaptive Control Based on RL and Improved DMPs)	None

Note: PPS: plantar pressure sensor, **AS:**Angle sensors, **AcS:** Acceleration sensors, **AFIC:** Adaptive Fuzzy Impedance Control, **ANN:** Artificial Neural Networks, **BCI:** brain computer interface, **CNN:** Convolutional Neural Networks, **DCNN:** Deep Convolutional Network, **DeLaN:** Deep Lagrangian Network, **DL:** deep learning network, **DMP:** Dynamic Motion Primitives, **GCNM:** Graph Convolutional Network Model, **HMC:** Human-Machine Coupled, **ML:** Machine Learning, **NMM:** Neuromuscular model, **NNC:** neural network control, **RL:** Reinforcement Learning, **SAC:** sensitivity amplification control

In the past two decades of power-assisted exoskeleton development, the overall technological progress can be loosely divided into three phases:

Before 2015, most studies, including partially commercialized exoskeletons, primarily employed control strategies based on human-machine interaction forces and position trajectory tracking. Motion detection utilized force sensors, displacement, and posture measurements, with a trend toward multi-sensor fusion. Intent recognition and prediction were mainly determined through thresholding and finite state machines, with some studies establishing dynamic exoskeleton or human musculoskeletal mathematical models. Relatively low detection accuracy, model precision, and simplistic control strategies resulted in poor anti-interference and collaborative performance during this period.

From 2015 to around 2019, bioelectrical signals—particularly brain-computer interfaces (BCIs)—were increasingly applied in sensing, improving signal latency and significantly enhancing motion intent detection accuracy and recognition rates. Nonlinear system modeling and uncertain disturbances began receiving more attention, with hybrid approaches combining partial models and algorithms such as Gaussian processes, Bayesian inference, and neural networks. Intelligent control strategies were extensively researched, improving control precision and real-time performance.

In the past five years, researchers have further focused on active disturbance rejection and human-exoskeleton adaptability, proposing and optimizing model-free recognition algorithms such as adaptive Dynamic Movement Primitives (DMP), Deep Convolutional Networks (DCNNs), and Graph Convolutional Network Models (GCNMs). Hybrid strategies integrating machine learning, reinforcement learning, and classical control methods have been developed, leading to significant advancements in trajectory tracking accuracy and human-machine collaborative control.

Nevertheless, we summarize current challenges in perception and control research for power-assisted exoskeletons to inspire future solutions:

(1) Human-Machine-Environment Perception

Existing sensors (e.g., IMUs, force/torque sensors, EMG, depth cameras) are susceptible to noise interference, and dynamic environments complicate data synchronization and fusion. Potential solutions include developing lightweight, low-power multi-modal sensor fusion algorithms (e.g., deep learning-based adaptive Kalman filtering) and fault-tolerant mechanisms for sensor failures. Enhancing adaptability to sudden obstacles or terrain changes remains a challenge.

(2) Motion Intent Recognition

Biological signals (e.g., EMG, EEG) exhibit high noise and intent recognition delays, impacting response speed. Solutions involve fusing multi-source signals (EMG + inertial + pressure distribution + vision) with spatiotemporal attention networks or predictive intent algorithms to improve accuracy. Individual differences (e.g., muscle activation patterns, movement habits) reduce model generalizability. Transfer learning frameworks could enable rapid adaptation with minimal user data.

(3) Motion Trajectory Prediction

Human motion's high nonlinearity and vulnerability to external disturbances (e.g., pushes, load variations) increase prediction uncertainty, especially during transitions or abrupt movements. Solutions may combine probabilistic graphical models (e.g., conditional random fields) with deep learning to quantify uncertainty. Additionally, online learning mechanisms could dynamically adjust prediction models based on real-time feedback to mitigate error accumulation.

(4) Collaborative Control Strategies

Balancing active assistance with unobstructed user autonomy remains unresolved. Safety and stability—such as emergency protocols for prediction errors—are critical. Multi-joint coordination and long-term comfort also require attention. While impedance control enhances compliance, fixed parameters limit adaptability to task or user state changes. Future work could develop reinforcement learning-based adaptive impedance control to optimize human-machine dynamic coupling.

In summary, power-assisted exoskeletons require breakthroughs in key technologies to advance human-machine collaboration. Future research should prioritize real-time perception-decision-execution optimization in dynamic environments, while balancing personalization, safety, energy efficiency, and cost. Promising directions include: Multi-modal data-driven adaptive algorithms, Human-in-the-loop learning mechanisms, and hardware-software co-design (e.g., neuromorphic computing chips) to address computational and power demands.

Acknowledgments

This work was supported by the Science and Technology Research Program of Chongqing Municipal Education Commission (Grant Nos. KJQN202001309, KJQN202301345), the Natural Science Foundation of Chongqing (No. cstc2021jcyj-msxmX0812), the Opening Project of Engineering Research Center of Chongqing Education Commission of China in Running and Maintenance of Robots (No. YWZX20220002).

References

1. Young, A. J., & Ferris, D. P. (2017). State of the Art and Future Directions for Lower Limb Robotic Exoskeletons. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 25(2), 171–182. doi:10.1109/tnsre.2016.2521160.
2. Aliman, N., Ramli, R., & Haris, S. (2017). Design and development of lower limb exoskeletons: A survey. Robotics and Autonomous Systems, 95, 102–116. https://doi.org/10.1016/j.robot.2017.05.013.
3. M. Fontana, R. Vertechy, S. Marcheschi, F. Salsedo and M. Bergamasco, "The Body Extender: A Full-Body Exoskeleton for the Transport and Handling of Heavy Loads," in IEEE Robotics & Automation Magazine, vol. 21, no. 4, pp. 34-44, Dec. 2014, doi: 10.1109/MRA.2014.2360287.
4. A. Zoss, H. Kazerooni and A. Chu, "On the mechanical design of the Berkeley Lower Extremity Exoskeleton (BLEEX)," 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems, Edmonton, AB, Canada, 2005, pp. 3465-3472, doi: 10.1109/IROS.2005.1545453.
5. A. B. Zoss, H. Kazerooni and A. Chu, "Biomechanical design of the Berkeley lower extremity exoskeleton (BLEEX)," in IEEE/ASME Transactions on Mechatronics, vol. 11, no. 2, pp. 128-138, April 2006, doi: 10.1109/TMECH.2006.871087.
6. S. Karlin, "Raiding Iron Man's closet [Geek Life]," in IEEE Spectrum, vol. 48, no. 8, pp. 25-25, August 2011, doi: 10.1109/MSPEC.2011.5960158.
7. HULC [EB/OL].[2025-01-10] https://bleex.me.berkeley.edu/project/hulc/.
8. C. J. Walsh, K. Pasch and H. Herr, "An autonomous, underactuated exoskeleton for load-carrying augmentation," 2006 IEEE/RSJ International Conference on Intelligent Robots and Systems, Beijing, China, 2006, pp. 1410-1415, doi: 10.1109/IROS.2006.281932.
9. Asbeck, A. T., Schmidt, K., & Walsh, C. J. (2015). Soft exosuit for hip assistance. Robotics and Autonomous Systems, 73, 102–110. doi:10.1016/j.robot.2014.09.025.

10. Ghan, J., Steger, R., & Kazerooni, H. (2006). Control and system identification for the Berkeley lower extremity exoskeleton (BLEEX). Advanced Robotics, 20(9), 989–1014. https://doi.org/10.1163/156855306778394012.
11. R. Steger, Sung Hoon Kim and H. Kazerooni, "Control scheme and networked control architecture for the Berkeley lower extremity exoskeleton (BLEEX)," Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006., Orlando, FL, 2006, pp. 3469-3476, doi: 10.1109/ROBOT.2006.1642232.
12. T. Hayashi, H. Kawamoto and Y. Sankai, "Control method of robot suit HAL working as operator's muscle using biological and dynamical information," 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems, Edmonton, AB, Canada, 2005, pp. 3063-3068, doi: 10.1109/IROS.2005.1545505.
13. Sczesny-Kaiser, Matthias et al. "HAL® exoskeleton training improves walking parameters and normalizes cortical excitability in primary somatosensory cortex in spinal cord injury patients." Journal of neuroengineering and rehabilitation vol. 12 68. 20 Aug. 2015, doi:10.1186/s12984-015-0058-9.
14. P. Neuhaus and H. Kazerooni, "Design and control of human assisted walking robot," Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No.00CH37065), San Francisco, CA, USA, 2000, pp. 563-569 vol.1, doi: 10.1109/ROBOT.2000.844113.
15. Esquenazi A, Talaty M, Packel A, Saulino M. The ReWalk powered exoskeleton to restore ambulatory function to individuals with thoracic-level motor-complete spinal cord injury. Am J Phys Med Rehabil. 2012 Nov;91(11):911-21. doi: 10.1097/PHM.0b013e318269d9a3.
16. Quintero HA, Farris RJ, Hartigan C, Clesson I, Goldfarb M. A Powered Lower Limb Orthosis for Providing Legged Mobility in Paraplegic Individuals. Top Spinal Cord Inj Rehabil. 2011;17(1):25-33. doi: 10.1310/sci1701-25.
17. eLEGs[EB/OL].[2025-01-10] https://bleex.me.berkeley.edu/project/elegs/.
18. Milia, Paolo et al. "Neurorehabilitation in paraplegic patients with an active powered exoskeleton (Ekso)." Digital Medicine 2 (2016): 163 - 168. DOI:10.4103/digm.digm_51_16.
19. L. Wang, S. Wang, E. H. F. van Asseldonk and H. van der Kooij, "Actively controlled lateral gait assistance in a lower limb exoskeleton," 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems, Tokyo, Japan, 2013, pp. 965-970, doi: 10.1109/IROS.2013.6696467.
20. S. Wang et al., "Design and Control of the MINDWALKER Exoskeleton," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 23, no. 2, pp. 277-286, March 2015, doi: 10.1109/TNSRE.2014.2365697.
21. S. Alabdulkarim, S. Kim, M.A. Nussbaum, Effects of exoskeleton design and precision requirements on physical demands and quality in a simulated overhead drilling task, Appl. Ergon. 80 (2019) 136–145, https://doi.org/10.1016/j.apergo.2019.05.014.
22. Chu, G. et al. (2014). The experiments of wearable robot for carrying heavy-weight objects of shipbuilding works. 2014 IEEE International Conference on Automation Science and Engineering (CASE). doi:10.1109/coase.2014.6899445.
23. Hian Kai Kwa, J. H. Noorden, M. Missel, T. Craig, J. E. Pratt and P. D. Neuhaus, "Development of the IHMC Mobility Assist Exoskeleton," 2009 IEEE International Conference on Robotics and Automation, Kobe, Japan, 2009, pp. 2556-2562, doi: 10.1109/ROBOT.2009.5152394.
24. S. Toyama and G. Yamamoto, "Development of Wearable-Agri-Robot ~mechanism for agricultural work~," 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems, St. Louis, MO, USA, 2009, pp. 5801-5806, doi: 10.1109/IROS.2009.5354265.

25. Chinanews.com. [EB/OL].[2020-04-22] https://www.chinanews.com/sh/shipin/cns-d/2020/04-22/news854490.shtml.
26. Yan T, Cempini M, Oddo CM, Vitiello N. Review of assistive strategies in powered lower-limb orthoses and exoskeletons. Robot Autonom Syst. 2015;64:120–36. https://doi.org/10.1016/j.robot.2014.09.032.
27. Ahmed AIA, Cheng H, Lin X, Omer M, Atieno JM (2016) Survey of On-line Control Strategies of Human-Powered Augmentation Exoskeleton Systems. Adv Robot Autom 5: 158. doi: 10.4172/2168-9695.1000158.
28. Baud, Romain et al. "Review of control strategies for lower-limb exoskeletons to assist gait." Journal of NeuroEngineering and Rehabilitation 18 (2021): n. pag. DOI:10.1186/s12984-021-00906-3.
29. X. Luo, Y. Ma, Z. Cai, T. Zhou, X. Liu and Y. Long, "State-of-the-art Research in Perception and Control of Lower Limb Exoskeletons: A Systematic Review," 2024 3rd International Conference on Service Robotics (ICoSR), Hangzhou, China, 2024, pp. 135-142, doi: 10.1109/ICoSR63848.2024.00037.
30. K. Yamamoto, M. Ishii, H. Noborisaka and K. Hyodo, "Stand alone wearable power assisting suit - sensing and control systems," RO-MAN 2004. 13th IEEE International Workshop on Robot and Human Interactive Communication (IEEE Catalog No.04TH8759), Kurashiki, Okayama, Japan, 2004, pp. 661-666, doi: 10.1109/ROMAN.2004.1374841.
31. Kyuhwa Lee, et al. A brain-controlled exoskeleton with cascaded event-related desynchronization classifiers. Robot. Auton. Syst. 90, C (April 2017), 15–23. https://doi.org/10.1016/j.robot.2016.10.005.
32. Wang Lulu, Hu Xin, Hu Jie, etc Research on the Control System of an Upper Limb Exoskeleton Rehabilitation Robot [J]. Journal of Biomedical Engineering, 2016, 33 (6): 1168-1175. DOI: 10.7507/1001-5515.2016185.
33. N. Mir-Nasiri and H. S. Jo, "Tactile human interface with weight supporting lower limb exoskeleton," 2018 4th International Conference on Control, Automation and Robotics (ICCAR), Auckland, New Zealand, 2018, pp. 131-135, doi: 10.1109/ICCAR.2018.8384657.
34. D. Copaci, F. Martín, L. Moreno and D. Blanco, "SMA Based Elbow Exoskeleton for Rehabilitation Therapy and Patient Evaluation," in IEEE Access, vol. 7, pp. 31473-31484, 2019, doi: 10.1109/ACCESS.2019.2902939.
35. McMullen DP, Hotson G, Katyal KD, et al. Demonstration of a semi-autonomous hybrid brain-machine interface using human intracranial EEG, eye tracking, and computer vision to control a robotic upper limb prosthetic. IEEE Trans Neural Syst Rehabil Eng. 2014 Jul;22(4):784-96. doi: 10.1109/TNSRE.2013.2294685.
36. B. Shen, J. Li, F. Bai and C. -M. Chew, "Motion intent recognition for control of a lower extremity assistive device (LEAD)," 2013 IEEE International Conference on Mechatronics and Automation, Takamatsu, Japan, 2013, pp. 926-931, doi: 10.1109/ICMA.2013.6618039.
37. S. Wang et al., "Design and Control of the MINDWALKER Exoskeleton," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 23, no. 2, pp. 277-286, March 2015, doi: 10.1109/TNSRE.2014.2365697.
38. P. Zhang and J. Zhang, "Deep learning analysis based on multi-sensor fusion data for hemiplegia rehabilitation training system for stoke patients," Robotica, vol. 40, no. 3, pp. 780–797, Mar. 2022. https://doi.org/10.1017/ s0263574721000801.
39. P. Zhang, J. Zhang and A. Elsabbagh, "Lower Limb Motion Intention Recognition Based on sEMG Fusion Features," in IEEE Sensors Journal, vol. 22, no. 7, pp. 7005-7014, 1 April1, 2022, doi: 10.1109/JSEN.2022.3146446.

40. Zheng, Yi, et al. "Research on motion pattern recognition of exoskeleton robot based on multimodal machine learning model." Neural Computing and Applications 32 (2020): 1869-1877. Doi: 10.1007/s00521-019-04567-1.
41. J. C. Arceo, L. Yu and S. Bai, "Robust Sensor Fusion and Biomimetic Control of a Lower-Limb Exoskeleton With Multimodal Sensors," in IEEE Transactions on Automation Science and Engineering, doi: 10.1109/ TASE.2024.3421318.
42. Zhang Y, Cao G, Ling Z, Li W, Cheng H, He B, Cao S and Zhu A (2021) A Multi-Information Fusion Method for Gait Phase Classification in Lower Limb Rehabilitation Exoskeleton. Front. Neurorobot. 15:692539. doi: 10.3389/fnbot.2021.692539.
43. Q. Guo, H. Zhan and J. Zhang, "Deep Lagrangian Network Learning and Control of Robotic Exoskeleton Based on Multi-Sensor-Cyber Information Fusion," in IEEE Transactions on Industrial Cyber-Physical Systems, vol. 2, pp. 331-339, 2024, doi: 10.1109/TICPS.2024.3437347.
44. H. Huang, F. Zhang, L. J. Hargrove, Z. Dou, D. R. Rogers and K. B. Englehart, "Continuous Locomotion-Mode Identification for Prosthetic Legs Based on Neuromuscular–Mechanical Fusion," in IEEE Transactions on Biomedical Engineering, vol. 58, no. 10, pp. 2867-2875, Oct. 2011, doi: 10.1109/TBME.2011.2161671.
45. Young AJ, Kuiken TA, Hargrove LJ. Analysis of using EMG and mechanical sensors to enhance intent recognition in powered lower limb prostheses. J Neural Eng. 2014 Oct;11(5):056021. doi: 10.1088/1741-2560/11/5/056021.
46. K. A. Strausser and H. Kazerooni, "The development and testing of a human machine interface for a mobile medical exoskeleton," 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems, San Francisco, CA, USA, 2011, pp. 4911-4916, doi: 10.1109/IROS.2011.6095025.
47. De Rossi SM, Vitiello N, Lenzi T, Ronsse R, Koopman B, Persichetti A, Vecchi F, Ijspeert AJ, van der Kooij H, Carrozza MC. Sensing pressure distribution on a lower-limb exoskeleton physical human-machine interface. Sensors (Basel). 2011;11(1):207-27. doi: 10.3390/s110100207.
48. J. F. Veneman, et al. "Design and Evaluation of the LOPES Exoskeleton Robot for Interactive Gait Rehabilitation," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 15, no. 3, pp. 379-386, Sept. 2007, doi: 10.1109/TNSRE.2007.903919.
49. J. Gancet et al., "MINDWALKER: Going one step further with assistive lower limbs exoskeleton for SCI condition subjects," 2012 4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob), Rome, Italy, 2012, pp. 1794-1800, doi: 10.1109/BioRob.2012.6290688.
50. H. Kazerooni, J. . -L. Racine, Lihua Huang and R. Steger, "On the Control of the Berkeley Lower Extremity Exoskeleton (BLEEX)," Proceedings of the 2005 IEEE International Conference on Robotics and Automation, Barcelona, Spain, 2005, pp. 4353-4360, doi: 10.1109/ROBOT.2005.1570790.
51. ISHII, M., YAMAMOTO, K., & HYODO, K. (2006). Stand Alone Wearable Power Assisting Suit (Development and Availability). Transactions of the Japan Society of Mechanical Engineers Series C, 72(715), 857–864. doi:10.1299/kikaic.72.857.
52. Kawamoto H, Taal S, Niniss H, Hayashi T, Kamibayashi K, Eguchi K, Sankai Y. Voluntary motion support control of Robot Suit HAL triggered by bioelectrical signal for hemiplegia. Annu Int Conf IEEE Eng Med Biol Soc. 2010;2010:462-6. doi: 10.1109/IEMBS.2010.5626191.
53. PAPINI G P R, AVIZZANO C. Transparent force control for Body Extender[J]. 2012 IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication, 2012, 11 1: 0. DOI:10.1109/ROMAN.2012.6343744.

54. Ai, Q., Ding, B., Liu, Q., & Meng, W. (2016). A Subject-Specific EMG-Driven Musculoskeletal Model for Applications in Lower-Limb Rehabilitation Robotics. International Journal of Humanoid Robotics, 13(03), 1650005. doi:10.1142/s0219843616500055.
55. Wu, A. R., Dzeladini, F., Brug, T. J. H., Tamburella, F., Tagliamonte, N. L., van Asseldonk, E. H. F., … Ijspeert, A. J. (2017). An Adaptive Neuromuscular Controller for Assistive Lower-Limb Exoskeletons: A Preliminary Study on Subjects with Spinal Cord Injury. Frontiers in Neurorobotics, 11. doi:10.3389/fnbot.2017.00030.
56. Ao, D., Song, R., & Gao, J. (2017). Movement Performance of Human–Robot Cooperation Control Based on EMG-Driven Hill-Type and Proportional Models for an Ankle Power-Assist Exoskeleton Robot. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 25(8), 1125–1134. doi:10.1109/tnsre.2016.2583464.
57. Y. Li and S. S. Ge, "Human–Robot Collaboration Based on Motion Intention Estimation," in IEEE/ASME Transactions on Mechatronics, vol. 19, no. 3, pp. 1007-1014, June 2014, doi: 10.1109/TMECH.2013.2264533.
58. Tran, HT., Cheng, H., Lin, X. et al. The relationship between physical human-exoskeleton interaction and dynamic factors: using a learning approach for control applications. Sci. China Inf. Sci. 57, 1–13 (2014). https://doi.org/10.1007/s11432-014-5203-8.
59. G. Wang, Y. Liu, Y. Shen, Y. Chen, K. Liu and Z. Sun, "SEMG-based multi-joints motion estimation of lower limb utilizing deep convolutional neural network", Proc. IEEE Int. Conf. Real-Time Comput. Robot. (RCAR), pp. 13-18, Jul. 2022.
60. M. T. N. Truong, A. E. A. Ali, D. Owaki and M. Hayashibe, "EMG-based estimation of lower limb joint angles and moments using long short-term memory network", Sensors, vol. 23, no. 6, pp. 3331, Mar. 2023.
61. A. Jamsrandorj, K. S. Kumar, M. Z. Arshad, K.-R. Mun and J. Kim, "Deep learning networks for view-independent knee and elbow joint angle estimation", Proc. 44th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), pp. 2703-2707, Jul. 2022.
62. L. Chen and D. Hu, "A deep learning control strategy of IMU-based joint angle estimation for hip power-assisted swimming exoskeleton", IEEE Sensors J., vol. 23, no. 13, pp. 15058-15070, Jul. 2023.
63. N. Sun, M. Cao, Y. Chen, Y. Chen, J. Wang, Q. Wang, et al., "Continuous estimation of human knee joint angles by fusing kinematic and myoelectric signals", IEEE Trans. Neural Syst. Rehabil. Eng., vol. 30, pp. 2446-2455, 2022.
64. X. Wang, D. Dong, X. Chi, S. Wang, Y. Miao, M. An, et al., "SEMG-based consecutive estimation of human lower limb movement by using multi-branch neural network", Biomed. Signal Process. Control, vol. 68, Jul. 2021.
65. Y. Lu, H. Wang, B. Zhou, C. Wei and S. Xu, "Continuous and simultaneous estimation of lower limb multi-joint angles from sEMG signals based on stacked convolutional and LSTM models", Exp. Syst. Appl., vol. 203, Oct. 2022.
66. V. Hernandez, D. Dadkhah, V. Babakeshizadeh and D. Kulić, "Lower body kinematics estimation from wearable sensors for walking and running: A deep learning approach", Gait Posture, vol. 83, pp. 185-193, Jan. 2021.
67. S. Wang, H. Tang, L. Gao and Q. Tan, "Continuous estimation of human joint angles from sEMG using a multi-feature temporal convolutional attention-based network", IEEE J. Biomed. Health Informat., vol. 26, no. 11, pp. 5461-5472, Nov. 2022.
68. T. Zebin, M. Sperrin, N. Peek and A. J. Casson, "Human activity recognition from inertial sensor time-series using batch normalized deep LSTM recurrent networks," 2018 40th Annual International Conference of the

IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, 2018, pp. 1-4, doi: 10.1109/EMBC.2018.8513115.

69. Ma, X.; Liu, Y.; Song, Q.; Wang, C. Continuous Estimation of Knee Joint Angle Based on Surface Electromyography Using a Long Short-Term Memory Neural Network and Time-Advanced Feature. Sensors 2020, 20, 4966. https://doi.org/10.3390/s20174966.
70. O. Harib et al., "Feedback Control of an Exoskeleton for Paraplegics: Toward Robustly Stable, Hands-Free Dynamic Walking," in IEEE Control Systems Magazine, vol. 38, no. 6, pp. 61-87, Dec. 2018, doi: 10.1109/MCS.2018.2866604.
71. Qin, T., Yang, Y., Wen, B. et al. Research on human gait prediction and recognition algorithm of lower limb-assisted exoskeleton robot. Intel Serv Robotics 14, 445–457 (2021). https://doi.org/10.1007/s11370-021-00367-6.
72. CHENG Hong,HUANG Rui,QIU Jing,et a1.A survey of recent advances in human-robot intelligent systems [J].CAAI transactions On intelligent systems,2020,15(2):386-398.DOI: 10.11992/tis.201912001.
73. ZHOU Zhiyong, QIAN Wei, DING Jiatao, XIAO Xiaohui, GUO Zhao. Online Gait Trajectory Planning of a Knee Exoskeleton Robot Based on Kernelized Movement Primitives[J]. ROBOT, 2021, 43(5): 557-566. DOI: 10.13973/j.cnki.robot.200528.
74. X. Wu, D. -X. Liu, M. Liu, C. Chen and H. Guo, "Individualized Gait Pattern Generation for Sharing Lower Limb Exoskeleton Robot," in IEEE Transactions on Automation Science and Engineering, vol. 15, no. 4, pp. 1459-1470, Oct. 2018, doi: 10.1109/TASE.2018.2841358.
75. Baud, R., Manzoori, A.R., Ijspeert, A. et al. Review of control strategies for lower-limb exoskeletons to assist gait. J NeuroEngineering Rehabil 18, 119 (2021). https://doi.org/10.1186/s12984-021-00906-3.
76. Ma Chaojie, Gan Yi, Sun Fujia Lower limb exoskeleton assisted mechanism and sliding mode gait trajectory tracking control method [J]. Modeling and Simulation, 2023, 12 (1): 559-572 https://doi.org/10.12677/MOS.2023.121052.
77. Liu Yang, Peng Shiguo, Du Yuxiao, etc Dynamic modeling and gait tracking LQR control of lower limb exoskeleton robot [J]. Computer Simulation, 2021,38 (4): 296-301. DOI: 10.3969/j.issn.1006-9348.2021.04.060.
78. Jaime Arcos-Legarda, John Cortes-Romero, Andres Tovar, Robust compound control of dynamic bipedal robots, Mechatronics, Volume 59, 2019, Pages 154-167, https://doi.org/10.1016/j.mechatronics.2019.04.002.
79. Tanaka, N., Matsushita, S., Sonoda, Y., Maruta, Y., Fujitaka, Y., Sato, M., … Okamura, H. (2018). Effect of Stride Management Assist Gait Training for Poststroke Hemiplegia: A Single Center, Open-Label, Randomized Controlled Trial. Journal of Stroke and Cerebrovascular Diseases. doi:10.1016/j.jstrokecerebrovasdis.2018.
80. W. -Z. Li, G. -Z. Cao and A. -B. Zhu, "Review on Control Strategies for Lower Limb Rehabilitation Exoskeletons," in IEEE Access, vol. 9, pp. 123040-123060, 2021, doi: 10.1109/ACCESS.2021.3110595.
81. G. Aguirre-Ollinger, J. E. Colgate, M. A. Peshkin and Ambarish Goswami, "A 1-DOF assistive exoskeleton with virtual negative damping: effects on the kinematic response of the lower limbs," 2007 IEEE/RSJ International Conference on Intelligent Robots and Systems, San Diego, CA, USA, 2007, pp. 1938-1944, doi: 10.1109/IROS.2007.4399147.
82. U. Nagarajan, G. Aguirre-Ollinger and A. Goswami, "Integral Admittance Shaping for exoskeleton control," 2015 IEEE International Conference on Robotics and Automation (ICRA), Seattle, WA, USA, 2015, pp. 5641-5648, doi: 10.1109/ICRA.2015.7139989.
83. M. Bernhardt, M. Frey, G. Colombo and R. Riener, "Hybrid force-position control yields cooperative behaviour of the rehabilitation robot LOKOMAT," 9th International Conference on Rehabilitation Robotics, 2005. ICORR 2005., Chicago, IL, USA, 2005, pp. 536-539, doi: 10.1109/ICORR.2005.1501159.

84. D. Zanotto, P. Stegall and S. K. Agrawal, "ALEX III: A novel robotic platform with 12 DOFs for human gait training," 2013 IEEE International Conference on Robotics and Automation, Karlsruhe, Germany, 2013, pp. 3914-3919, doi: 10.1109/ICRA.2013.6631128.
85. Zhao Zongsheng, Cheng Jinshi, Wu Hongda, Tian Sican, Zhang Han Research and Application Progress of Force Control Technology for Robots [J]. Artificial Intelligence and Robotics Research, 2023, 12(4): 292-300. DOI: 10.12677/airr.2023.124032.
86. Song, G., Huang, R., Qiu, J. et al. Model-based Control with Interaction Predicting for Human-coupled Lower Exoskeleton Systems. J Intell Robot Syst 100, 389–400 (2020). https://doi.org/10.1007/s10846-020-01200-5.
87. R. Zheng, Z. Yu, H. Liu, Z. Zhao, J. Chen and L. Jia, "Sensitivity Adaptation of Lower-Limb Exoskeleton for Human Performance Augmentation Based on Deep Reinforcement Learning," in IEEE Access, vol. 11, pp. 36029-36040, 2023, doi: 10.1109/ACCESS.2023.3265895.
88. K. H. Low, Xiaopeng Liu and Haoyong Yu, "Development of NTU wearable exoskeleton system for assistive technologies," IEEE International Conference Mechatronics and Automation, 2005, Niagara Falls, ON, Canada, 2005, pp. 1099-1106 Vol. 2, doi: 10.1109/ICMA.2005.1626705.
89. Zhang, X., Wang, G., Yuan, P. et al. A Control Strategy for Maintaining Gait Stability and Reducing Body-Exoskeleton Interference Force in Load-Carrying Exoskeleton. J Intell Robot Syst 97, 287–298 (2020). https://doi.org/10.1007/s10846-019-01043-9.
90. X. Wang, H. Wang and Y. Tian, "Gait planning and hybrid model based tracking control of lower extremity exoskeleton," 2016 35th Chinese Control Conference (CCC), Chengdu, China, 2016, pp. 6019-6024, doi: 10.1109/ChiCC.2016.7554302.
91. Jatsun, S., Savin, S., Yatsun, A. (2018). Motion Control Algorithm for a Lower Limb Exoskeleton Based on Iterative LQR and ZMP Method for Trajectory Generation. In: Husty, M., Hofbaur, M. (eds) New Trends in Medical and Service Robots. MESROB 2016. Mechanisms and Machine Science, vol 48. Springer, Cham. https://doi.org/10.1007/978-3-319-59972-4_22.
92. Servick, K. (2014). Kickoff looms for demo of brain-controlled machine. Science, 344(6188), 1069–1070. doi:10.1126/science.344.6188.1069.
93. B. J. Edelman, B. Baxter and B. He, "EEG Source Imaging Enhances the Decoding of Complex Right-Hand Motor Imagery Tasks," in IEEE Transactions on Biomedical Engineering, vol. 63, no. 1, pp. 4-14, Jan. 2016, doi: 10.1109/TBME.2015.2467312.
94. Yong He, et al, An sEMG based adaptive method for human-exoskeleton collaboration in variable walking environments, Biomedical Signal Processing and Control, Volume 74, 2022, 103477, https://doi.org/10.1016/j.bspc.2021.103477.
95. Song, T.; Yan, Z.; Guo, S.; Li, Y.; Li, X.; Xi, F. Review of sEMG for Robot Control: Techniques and Applications. Appl. Sci. 2023, 13, 9546. doi.org/10.3390/app13179546.
96. W. Li et al., "The Human–Machine Interface Design Based on sEMG and Motor Imagery EEG for Lower Limb Exoskeleton Assistance System," in IEEE Transactions on Instrumentation and Measurement, vol. 73, pp. 1-14, 2024, Art no. 6502914, doi: 10.1109/TIM.2024.3375980.
97. Yang S, Li M, Wang J, Shi Z, He B, Xie J and Xu G (2023) A low-cost and portable wrist exoskeleton using EEG-sEMG combined strategy for prolonged active rehabilitation. Front. Neurorobot. 17:1161187. doi: 10.3389/fnbot.2023.1161187.
98. W. Sun, J. -W. Lin, S. -F. Su, N. Wang and M. J. Er, "Reduced Adaptive Fuzzy Decoupling Control for Lower Limb Exoskeleton," in IEEE Transactions on Cybernetics, vol. 51, no. 3, pp. 1099-1109, March 2021, doi: 10.1109/TCYB.2020.2972582.

99. Shuaishuai Han, Haoping Wang, Yang Tian, Nicolai Christov, Time-delay estimation based computed torque control with robust adaptive RBF neural network compensator for a rehabilitation exoskeleton, ISA Transactions, Volume 97, 2020, Pages 171-181, https://doi.org/10.1016/j.isatra.2019.07.030.
100. I. Kang, P. Kunapuli and A. J. Young, "Real-Time Neural Network-Based Gait Phase Estimation Using a Robotic Hip Exoskeleton," in IEEE Transactions on Medical Robotics and Bionics, vol. 2, no. 1, pp. 28-37, Feb. 2020, doi: 10.1109/TMRB.2019.2961749.
101. Siyang Yang, Jiang Han, Lian Xia, Ye-Hwa Chen, An optimal fuzzy-theoretic setting of adaptive robust control design for a lower limb exoskeleton robot system, Mechanical Systems and Signal Processing, Volume 141, 2020, 106706, https://doi.org/10.1016/j.ymssp.2020.106706.
102. Ali Foroutannia, et al. Adaptive fuzzy impedance control of exoskeleton robots with electromyography-based convolutional neural networks for human intended trajectory estimation, Mechatronics, Volume 91, 2023, 102952, https://doi.org/10.1016/j.mechatronics.2023.102952.
103. Lin, C.-J.; Sie, T.-Y. Design and Experimental Characterization of Artificial Neural Network Controller for a Lower Limb Robotic Exoskeleton. Actuators 2023, 12, 55. https://doi.org/10.3390/act12020055.
104. Rose, Lowell, Michael CF Bazzocchi, and Goldie Nejat. "A model-free deep reinforcement learning approach for control of exoskeleton gait patterns." Robotica 40.7 (2022): 2189-2214.
105. Ratnakumar, Neethan, et al. "Predicting sit-to-stand motions with a deep reinforcement learning based controller under idealized exoskeleton assistance." Multibody System Dynamics (2024): 1-18.
106. Tu, Xikai, et al. "A data-driven reinforcement learning solution framework for optimal and adaptive personalization of a hip exoskeleton." 2021 IEEE international conference on robotics and automation (ICRA). IEEE, 2021.
107. Goyal, Chinmayi. "Towards User-Driven Exoskeletal Assistive Control using Deep Reinforcement Learning." 2024 IEEE 15th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON). IEEE, 2024.
108. Dizor, R., A. Raj, and B. Gonzalez. "Deep reinforcement learning Control of an Avatar and exoskeleton." 2024 IEEE Research and Applications of Photonics in Defense Conference (RAPID). IEEE, 2024.
109. J. Weng, E. Hashemi and A. Arami, "Natural Walking With Musculoskeletal Models Using Deep Reinforcement Learning," in IEEE Robotics and Automation Letters, vol. 6, no. 2, pp. 4156-4162, April 2021
110. R. Zheng, Z. Yu, H. Liu, J. Chen, Z. Zhao and L. Jia, "End-to-End High-Level Control of Lower-Limb Exoskeleton for Human Performance Augmentation Based on Deep Reinforcement Learning," in IEEE Access, vol. 11, pp. 102340-102351, 2023, doi: 10.1109/ACCESS.2023.3317183.
111. Huang, L., Zheng, J., Gao, Y. et al. A Lower Limb Exoskeleton Adaptive Control Method Based on Model-free Reinforcement Learning and Improved Dynamic Movement Primitives. J Intell Robot Syst 111, 24 (2025). https://doi.org/10.1007/s10846-025-02230-7.
112. X. Wu, Y. Yuan, X. Zhang, C. Wang, T. Xu and D. Tao, "Gait Phase Classification for a Lower Limb Exoskeleton System Based on a Graph Convolutional Network Model," in IEEE Transactions on Industrial Electronics, vol. 69, no. 5, pp. 4999-5008, May 2022, doi: 10.1109/TIE.2021.3082067.
113. D. Lee, I. Kang, D. D. Molinaro, A. Yu and A. J. Young, "Real-Time User-Independent Slope Prediction Using Deep Learning for Modulation of Robotic Knee Exoskeleton Assistance," in IEEE Robotics and Automation Letters, vol. 6, no. 2, pp. 3995-4000, April 2021, doi: 10.1109/LRA.2021.3066973.
114. LI Chao, ZHANG Zhi, XIA Guihua, et al. Learning variable impedance control based on reinforcement learning. Journal of Harbin Engineering University, 2019, 40(2): 304-311. DOI: 10.11990/jheu.201803020.