Review

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Review

Control Algorithms for Medical Recovery Robots Used in Physiotherapy

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Abstract: Rehabilitation robots are an essential component of modern physical therapies, enabling personalized and intensive exercises for patients with neuromotor impairments. This paper provides a structured review of the main categories of control algorithms used in robotic therapy systems, with a focus on their ability to adapt to the patient's condition and variability during exercises. Adaptive control strategies, robust and predictive control, as well as intelligent algorithms based on machine learning and deep neural networks are analyzed. Special attention is paid to hybrid control schemes, as well as techniques that integrate surface electromyography (sEMG) signals and virtual constraints (Virtual Fixtures). Each control category is discussed in light of relevant recent works, highlighting the advantages, implementation challenges and clinical implications. The comparative analysis highlights the upward trend towards hybrid and data-driven methods, which allow for real-time personalization, increased robustness and improved functional outcomes. The paper concludes with a presentation of the main research challenges, such as real-time adaptation to nonlinear dynamics, safety in human–robot interaction, and interpretability of learning-based control strategies in a clinical context.

Keywords: rehabilitation robots; control algorithms; kinetotherapy; adaptive control; predictive control; robust control; hybrid control; machine learning; surface electromyography

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1. Introduction

In recent decades, technology has begun to play an increasingly important role in the healthcare field, contributing not only to diagnosis or treatment, but also to the medical recovery process. In this context, robotic systems have gained popularity, especially in physiotherapy, where they can offer a precise, controlled and repeatable alternative to classic manual therapy methods.

Motor recovery is a complex process, requiring personalized exercises and constant supervision, aspects that can be difficult to support with human intervention alone. Rehabilitation robots meet these challenges through their ability to execute precise, repeatable and adjustable movements according to the patient's needs. At the same time, they can monitor biomechanical parameters in real time and adapt therapy automatically, which contributes to increasing the efficiency of the recovery process.

A key element in the operation of these robotic systems is the control algorithms. They govern how the robot interacts with the patient, determining the level of assistance, resistance, adaptability and safety during exercises. The correct choice and implementation of these algorithms directly influences the success of the therapy, the impact on the patient and the ability to personalize the treatment.

In the current context, there is a transition from classical control methods, such as PID control or rigid pre-programmed trajectories, to advanced algorithms that incorporate artificial intelligence, machine learning and adaptive control. These new approaches allow the robot to react dynamically to patient behavior, learn from collected data and optimize therapy in real time.

The aim of this paper is to provide a comprehensive analysis of the current state of research on control algorithms used in medical rehabilitation robots used in physiotherapy, with a focus on the classification, functionality, advantages and challenges associated with each type of algorithm. In addition, future research directions and expected innovations in this field with high development potential will be highlighted.

2. Medical Rehabilitation Robots in Physiotherapy

2.1. Classification of Rehabilitation Robots

Robots used in physical therapy can be classified based on how they interact with the patient and the degree of autonomy or control they provide during therapy. They generally fall into three main categories: passive, active, and hybrid robots.

Passive robots provide mechanical support to the patient without actively generating movement. They are typically used to guide or support limbs during exercise, allowing the patient to perform desired movements with minimal assistance. Although they do not apply their own forces, these robots may include sensors to monitor position, speed, and forces involved in the exercise, data that can be useful in assessing the patient's progress.

Active robots, instead, are capable of generating controlled movements, guided by control algorithms. They can actively assist the patient by applying forces, correcting the trajectory and adapting the movement according to the patient's response. Active robots are essential in cases where the patient has reduced or no motor capacity, such as following a stroke or spinal cord injury. The implementation of advanced control algorithms allows these systems to provide personalized and adaptive therapy.

Hybrid robots combines elements of the previous two types. For example, they can function passively in the early stages of therapy, and then become active as the patient gains strength and control. This versatility allows them to be used in a wider range of clinical applications and rehabilitation stages.

This classification is essential for choosing the appropriate type of robot depending on the patient's needs and the therapeutic objectives pursued. In addition, it significantly influences the selection of control algorithms to be implemented, depending on the complexity and dynamics of the patient-robot interaction.

2.2. Areas of Application

Medical rehabilitation robots are designed to cover a variety of therapeutic needs, depending on the affected area, the severity of the motor deficit and the nature of the condition. The main areas of application include upper limb rehabilitation, lower limb rehabilitation and recovery of neuromotor functions following central nervous system injuries.

Upper limb rehabilitation involves exercises targeting the shoulders, elbows, wrists and fingers. Robots dedicated to this segment are often used in post-stroke treatment, limb trauma or post-surgical functional recovery. Their aim is to restore mobility, muscle strength and fine motor coordination. Robotic systems provide repetitive, targeted and progressive exercises, adapted to the patient's performance level.

Lower limb rehabilitation aims to improve walking ability, balance and postural stability. This is essential for patients who have suffered spinal cord injuries, orthopedic trauma or neurological disorders such as Parkinson's disease. Robots for the lower limbs can include exoskeletons, gait support devices and robotic platforms that simulate the natural movements of human walking. These technologies allow patients to relearn walking in a safe and controlled environment.

Neurological recovery is another important area of application, targeting patients with central nervous system disorders, such as stroke, multiple sclerosis, cerebral palsy, or head trauma. In such cases, robots can be used to stimulate neuroplasticity through repetitive and assisted exercises that mimic natural movements and provide constant feedback.

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Each application area comes with specific requirements in terms of robot design, the degree of assistance provided, and the complexity of control algorithms. Consequently, understanding these applications is essential for designing efficient and safe systems.

2.3. Examples of Robotic Systems Used

In recent decades, numerous robotic systems have been developed and implemented in clinical practice to support the motor recovery of patients. These systems vary in complexity, the degree of interaction with the patient, and the type of conditions targeted. Some of the most representative examples used in the field of robotic-assisted physiotherapy are:

2.3.1. Armeo®Spring/Power

The Armeo platform, developed by Hocoma, is a system designed for upper limb rehabilitation. The Armeo Spring version offers passive gravity-assisted support, making it ideal for patients in the early stages of therapy. In contrast, the Armeo Power integrates active movement control and interactive visual feedback, allowing for personalized exercises based on the patient's level. The system is often used in post-stroke recovery and neurological injuries.

2.3.2. Lokomat®

Also from Hocoma's portfolio, Lokomat is one of the most widely used robotic systems for gait rehabilitation. It consists of a robotic exoskeleton mounted on a treadmill, which allows controlled training of the lower limbs during walking. The system adjusts resistance and assistance in real time, depending on the patient's performance, being extremely useful in the rehabilitation of patients with spinal cord injuries, trauma or neurodegenerative diseases.

2.3.3. MIT-Manuscript

Originally designed at the Massachusetts Institute of Technology, MIT-Manus is one of the pioneers of rehabilitation robotics. Designed for upper limb rehabilitation, this robot allows repetitive movements to be performed in controlled trajectories, with the ability to adjust the level of assistance based on the patient's progress. MIT-Manus has been the basis of many clinical studies that have demonstrated the effectiveness of robotic therapy in post-stroke recovery.

2.3.4. ReWalk and HAL (Hybrid Assistive Limb)

These wearable exoskeletons are designed to assist patients with partial or complete paralysis in walking. ReWalk, developed in Israel, is used primarily by paraplegic patients and allows them to walk upright using sensors and a built-in control system. HAL, developed in Japan, relies on bioelectric signals detected in the skin, allowing intuitive control of the robot's movement. These systems represent the state of the art in restoring mobility in severe conditions.

These examples highlight the technological diversity that currently exists and how robotic solutions are adapted to different types of therapies, levels of motor impairment and patient needs. The implementation of control algorithms specific to each system contributes decisively to the efficiency and safety of the therapeutic process.

3. Control Algorithms Used in Rehabilitation Robots

In recent years, the increasingly sophisticated requirements of medical rehabilitation have driven the development of new control methods or the improvement of existing ones. Recent research focuses on real-time adaptation to patient variations, the integration of artificial intelligence, and the management of uncertainties inherent in human-robot interaction. A well-designed control algorithm contributes to:

- Maintaining safety during physical interaction between the robot and the patient;
- Providing an appropriate level of assistance, resistance, or freedom of movement;
- Monitoring and interpretation of biomechanical data recorded during therapy;
- Improving performance based on feedback obtained (in the case of adaptive control or machine learning).

3.1. Classical Control Algorithms

Classical control algorithms were first used in the design of robotic systems, including those for rehabilitation, due to their simplicity, stability, and ease of implementation. Classical control algorithms are PID and LQR. Although they are less flexible in the face of complex variations in the environment or patient behavior, these algorithms remain a core component in many applications, and recent research has adapted them to better respond to the dynamics of clinical interaction.

An improved version of PID control was proposed in [1], where it was adapted to compensate for dynamic variations generated by unpredictable patient movements. Thus, algorithmic modifications allow a faster reaction to perturbations caused by human interaction [1]. Zhou et al. [2] integrated a neuro-PID into the control loop of an elbow exoskeleton, using a back-propagation neural network to estimate and automatically compensate for external forces. Tests showed high tracking performance even in the presence of variable friction [2]. However, PID control only modifies its gains manually or through external scheduling schemes, so it does not respond spontaneously to changes in patient characteristics such as spasticity or fatigue. Also, in the presence of highly nonlinear behaviors, the PID provides only an approximate response, and tracking errors can increase significantly.

Researchers [3] optimized the LQR algorithm using modern numerical techniques to ensure superior stability under complex clinical conditions. They reported that the optimized LQR leads to a significant reduction in tracking errors [3]. LQR was also used in [4], where the authors applied a Gain-Scheduled LQR in a walking robot, adjusting the gain parameter according to the phase of the gait cycle to improve both stability and energy efficiency. The study reported an energy saving of approximately 12% compared to a fixed LQR [4]. Despite some advantages, LQR control critically depends on the fidelity of the dynamic model, and patient-robot perturbations or variations can lead to uneven performance. In both the case of PID and LQR control, to overcome the shortcomings, it is recommended to supplement it with adaptive, predictive or robust modules, or even integrate hybrid schemes that combine the strengths of each controller.

3.1.1. Practical Applications in Rehabilitation

PID algorithms are among the most widely used algorithms in the motion control of rehabilitation robots, due to their simplicity of implementation and ability to maintain system stability in the face of moderate load variations. In particular, these algorithms are frequently used for position and force control in passive or semi-active robotic systems.

A significant example is the implementation of PID control in the Lokomat rehabilitation system, used for gait recovery in patients with neurological injuries. PID control is used to maintain the planned trajectory of the lower limbs, constantly adjusting the robot movements according to deviations from the trajectory [5]. The PID control system ensures the tracking of a predetermined trajectory during gait training, maintaining patient stability and comfort [6]. Also, in a study by Nizamis et al. (2020), a PID controller was used to manage the interaction between a robotic exoskeleton for hand rehabilitation and the patient, ensuring a constant assist force [7].

3.1.2. Advantages and Limitations for PID Control Algorithms

Advantages:

- Simple implementation;
- Fast response in linear or weakly varying systems;

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– Easy to adjust according to the patient's needs.

Limitations:

– It does not adapt to the patient's dynamic variations;
– Can become unstable in systems with high delay or pronounced nonlinearity;
– Does not learn from the patient's previous behaviors.

Although simple to implement, PID control faces difficulties when it has to respond to variations in patient behavior or unpredictable interactions. PID control algorithms are used in controlling motors that provide standardized movements in devices such as Lokomat or ArmeoSpring, for repetitive exercises.

3.1.3. Advantages and Limitations for LQR Control Algorithms

Advantages:

– Provides an optimal balance between control accuracy and energy consumption;
– It is effective in well-modeled systems, such as exoskeletons with predictable loads.

Limitations:

– It requires a precise mathematical model of the system;
– Sensitive to uncertainties and nonlinear dynamic variations;
– It is not easy to apply in the rehabilitation of patients with unpredictable motor responses.

The LQR control algorithm can be used in systems with exoskeletons or robotic arms where the trajectory is known and precise (e.g. upper limb rehabilitation in advanced phases).

Even though classical algorithms are sometimes considered outdated, in combination with modern sensors and feedback strategies, they can constitute a solid basis for effective hybrid solutions in medical rehabilitation.

3.2. Adaptive Control

Unlike classical control, which assumes well-defined operating conditions, adaptive control is designed to deal with uncertainties and variations in system dynamics, which are essential aspects in rehabilitation therapy, where each patient responds differently to treatment. Adaptive control allows for automatic adjustment of algorithm parameters in real time, depending on the system response or changes in patient behavior. It is ideal for situations where the exact model of the system is not known or varies over time. In principle, a reference (ideal) model is used and the controller parameters are continuously updated to track this model. Adjustments are based on the differences between the actual and desired output.

To cope with inter-individual variations and uncertainties in the system, adaptive control has evolved rapidly. Thus, several approaches to adaptive control are found, such as:

1. Adaptive control based on Machine Learning (ML)

In [8], a simple neural network is trained online to estimate dynamic parameters and adjust gains in the admittance loop, with fast response to patient changes. In experiments on healthy volunteers, the authors demonstrated that the network converges to stable parameters in less than 2 s and maintains tracking error below 3% even under conditions of rapid variations in the patient's muscle load, which is essential for physiotherapy sessions where conditions change frequently [8]. This approach requires significant computational resources for open-loop training, possibly limiting the control frequency, and performance on patients with very different profiles may decrease without additional retraining. In [9], the RL agent (DDPG) is used that adapts impedance in real time based on biometric feedback, improving walking performance by over 20% [9]. However, the RL policy can explore unexpected behaviors in the learning phase, requiring long training and validation periods. Also in [10] a decentralized architecture with RBFNN is used for the estimation of exogenous forces and adaptive adjustment of gains, increasing the safety of the interaction. Each control loop at the

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shoulder, elbow or wrist level has its own RBFNN, which allows the estimation and compensation of external forces specific to each segment. Thus, the controller no longer has to "learn" the dynamics of the entire arm simultaneously, but only of a part, accelerating the convergence of adaptive gains [10]. Some difficulties would be due to the fact that each local network requires individual calibration, which can prolong the configuration and maintenance phase.

2. Adaptive control using EMG signals

These are used in [11] to modulate the impedance of the upper limb exoskeleton, ensuring a fine personalization of the therapy depending on the muscle effort. Adjusting the impedance of the exoskeleton based on the EMG signals allows the robot to provide the exact level of support needed by each patient, dynamically matching the real muscle force [11]. It is also possible to automatically adjust the virtual mass, damping and stiffness depending on the EMG amplitude, favoring the active participation of the patient. The virtual mass, damping and stiffness are continuously adjusted depending on the EMG amplitude, so that the active participation of the patient is increased and overload or under-assistance is avoided [12]. The use of a simple network that correlates EMG characteristics with the optimal level of assistance has also been studied, demonstrating rapid response to sudden variations in effort. A simple neural network, trained online to correlate EMG characteristics, provides updates of the order of tens of milliseconds when the patient changes his effort rapidly [9].

The use of EMG signals comes with some challenges, such as the fact that noise, motion artifacts or electrode contact variations can lead to erroneous estimates of the effort level, affecting the impedance modulation and potentially triggering inappropriate assistance. EMG preprocessing (filtering, feature extraction) introduces latencies that can compromise real-time response, especially to sudden variations in effort. An initial calibration step is required for each patient – normalization of EMG signals and adjustment of thresholds – which prolongs session preparation and reduces the scalability of clinical practice. Physiological variations (temperature changes, fatigue, hydration) can modify EMG characteristics and may require frequent recalibration to maintain performance.

3. Adaptive control based on Model-Free Sliding-Mode

Model-free Sliding-mode is used, enhanced with variable impedance and an adaptive law that prevents overestimation of the gain in the face of uncertainties. The adaptive law integrated with sliding-mode automatically adjusts the gains according to the system uncertainties [13]. But model-free Sliding-mode, even with an adaptive law, can generate significant chattering if not filtered correctly, affecting patient comfort. In [14], adaptive estimation of disturbances is used through high-order filtering and sliding-mode implementation, without knowledge of the plant structure. The high-order filtering component quickly and accurately detects the dynamic variations of the plant without requiring a mathematical model, which allows sliding-mode to effectively compensate for disturbances even in complex nonlinear systems [14]. However, high-order filtering must be precisely calibrated; too aggressive filters introduce latency, and too weak filters leave noise that disrupts the sliding condition. In [15], a sliding-mode algorithm with adaptive gains calculated from signals is used, ensuring robustness and high convergence speed. Sliding-mode with adaptive gains calculated directly from signals guarantees increased tolerance to uncertainties and a high convergence speed to the sliding surface, ensuring constant performance under variable conditions [15]. The problem would be that calculating adaptive gains directly from signals increases sensitivity to noise and may require additional filtering, affecting stability under real conditions.

4. Adaptive control based on the Lyapunov stability law

It is addressed in [16], where a 7 DOF kinematic model with realistic friction and 31 parameters adapted by Lyapunov stability conditions are used, achieving accurate trajectory tracking. The detailed kinematic model and Lyapunov adaptation allow the control to dynamically compensate for realistic friction effects and sudden load changes without performance loss [16] This method requires a detailed 7 DOF kinematic model and precise friction characterization, a time-consuming process prone to modeling errors, and tuning the 31 adaptive parameters according to Lyapunov conditions involves

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advanced expertise and numerous tests to fulfill the theoretical demonstration of stability in practice. In [17], a disturbance observer is integrated into the sliding-mode control loop, using Lyapunov criteria to ensure stability without an explicit model. The detailed kinematic model and Lyapunov adaptation allow the control to dynamically compensate for realistic friction effects and sudden load changes without performance loss [17]. However, the integration of the disturbance observer introduces computational latencies, and its performance critically depends on the calibration of the filters; inadequate tuning can compromise disturbance estimation and overall stability.

Adaptive control based on the Lyapunov stability law has limited robustness to dynamics not included in the model. Stability guarantees apply only to modeled uncertainties and unexpected nonlinearities or neglected dynamics can affect performance outside the conditions demonstrated theoretically.

There are important steps in improving adaptive control, but all of these approaches depend on real-time signals. Noise, artifacts, and transmission delay can significantly degrade adaptive performance. Excessive filtering reduces noise but introduces latency, and insufficient filtering maintains noise but distorts estimates. In essence, the common challenge is to find a balance between adaptability (personalization, rapid response) and robustness, stability (safety, clinical validation), without overloading computational resources or making the system too complicated to calibrate and operate in routine therapy.

3.2.1. Practical Applications in Rehabilitation

Adaptive control has become increasingly used in advanced robotic systems due to its ability to dynamically respond to variations in patient condition, biomechanical parameters, or individual motor behavior. This type of control is essential in personalized rehabilitation, allowing the robot to automatically adjust exercise intensity based on the user's progress.

Locomat pro Combo (Hocoma), G-Eo Evolution, Armeo Spring (Hocoma) use algorithms that adapt movements to the patient's ability and progressively improve the difficulty of the exercises. RehaStim uses algorithms that adjust functional electrical stimulation according to the patient's muscle response. The algorithm adapts to the patient's progress, adjusting the intensity and frequency of stimulation to support the recovery of limb movements.

3.2.2. Advantages and Limitations for Adaptive Control Algorithms

Advantages:

- Responds dynamically to changes in patient conditions;
- Allows personalized therapies;
- Increases safety by reacting to unforeseen variations.

Limitations:

- May require significant processing and high-precision sensors;
- Risk of instability if the algorithm is not well calibrated.

Adaptive control is used in robots that detect the patient's degree of cooperation and adjust the force/resistance in a personalized manner (e.g. MIT-Manus, Exo-Glove).

3.3. Intelligent Algorithms and Machine Learning

Machine learning (ML) and artificial intelligence (AI) are playing an increasingly important role in the field of robotic-assisted rehabilitation. Unlike classical control methods, intelligent algorithms can learn from data generated during therapy and dynamically adapt the robot's behavior according to the patient's needs [18].

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3.3.1. Types of Algorithms Used

a) **Artificial neural networks (ANN)**

They are used to estimate optimal trajectories, recognize patterns in patient movements, and adapt the level of assistance in real time. ANNs are capable of "learning" the complex relationships between robot commands and patient response [19].

b) **Reinforcement Learning (learning through reward)**

This method involves training an agent (robot) to make optimal decisions based on a reward function. In the context of rehabilitation, the robot is taught to improve the patient's movements by successive adjustments to trajectories, forces, or level of assistance [20].

c) **Support Vector Machines (SVM), K-Means, and other classification or clustering methods**

Used to analyze data collected during therapy sessions (e.g., classifying the patient's level of progress, automatically detecting patterns of fatigue or muscle stiffness) [21].

Artificial intelligence-based methods allow control systems to learn from clinical data and continuously adapt.

Different approaches to this method have been studied, such as:

1. Reinforcement Learning (RL)

In [22], RL is applied to control an exoskeleton during squat exercises, concluding that reward learning leads to continuous control adaptation [22]. Lee et al. [23] use a DDPG agent for real-time impedance tuning in spinal cord injury patients, reporting an improvement in walking performance [23]. In [24], Meta-RL is proposed for rapid personalization of the control policy, demonstrating that the system adapts to new patients with only a few training episodes [24]. Overall, the use of Reinforcement Learning techniques in the control of rehabilitation exoskeletons offers three complementary advantages: reward learning ensures a continuous and gradual adaptation of the control strategy as the patient evolves, the DDPG agent allows for real-time adjustment of impedance parameters to optimize walking assistance, and Meta-RL dramatically reduces calibration time, quickly personalizing the control policy for each new user. These approaches combine adaptive flexibility with clinical efficiency, paving the way for more individualized and responsive therapies to patient needs. However, the need for extensive training sessions, the opacity of learned policies, and the reliance on diverse data may limit the applicability of RL in clinical settings.

2. Deep learning

In [25], deep learning is combined with adaptive control for long-term stability, stating that the hybrid algorithm increases robustness under varying conditions [25] However, hybrid deep learning–adaptive methods require high computational resources and large volumes of training data, which may hinder real-time implementation. Caulcrick et al. [26] integrate neural networks for trajectory prediction, showing that deep learning-based models can predict subtle variations in patient behavior [26] but deep neural networks for trajectory prediction are "black boxes" that are difficult to interpret and sensitive to the quality and diversity of input data. In [27], a DRL with an internal MPC is implemented, using deep networks to optimize the prediction horizon, improving trajectory tracking [27]. One problem is that DRL with an internal MPC involves high architectural complexity and a high number of training episodes, increasing the tuning and validation time.

The major benefit of integrating deep learning into the control of rehabilitation robots is the ability to anticipate and dynamically adapt control strategies before deviations actually manifest themselves. Thus, the systems become more robust to patient behavior variability, can proactively adjust trajectories and force parameters, and provide much more accurate long-term trajectory tracking. In essence, deep learning brings advanced prediction and real-time adaptation, significantly improving the efficiency and personalization of therapy.

3. Active learning and assisted interaction

The article [28] proposes a system that integrates AI, ML and virtual sensors to personalize exercises in real time, promising continuous optimization of therapy sessions [28]. The difficulty would be that the integration of AI, ML and virtual sensors requires high complexity of implementation and data synchronization, increasing the risk of system errors. Taghvaei et al. [29] develop an adaptive admittance algorithm that adjusts its parameters based on the intention detected by ML, increasing patient engagement [29]. However, the adaptive admittance algorithm based on ML depends on the accuracy of intention detection, which can generate inadequate assistance in case of erroneous classifications. In [30], SVM and K-Means are used to classify the patient's progress, facilitating the automatic personalization of the exercise plan [30]. However, the use of SVM and K-Means for progress classification requires manual labeling and can be sensitive to noise and variation in patient data.

These methods transform robotic therapy into an interactive and patient-centered process, resulting in more efficient and personalized rehabilitation sessions. The main benefit is the dynamic and continuous personalization of therapy, which increases patient engagement and exercise effectiveness in real time.

4. Iterative algorithms based on backpropagation

The paper [31] proposes an iteratively trained multi-layer feedforward network capable of effectively compensating for spasmodic interference and accelerating the convergence of trajectory errors [31], but the multi-layer feedforward network requires extensive computational resources and data for iterative training, which may introduce latency and increase the complexity of the implementation. Zhang et al. [32] apply an iterative CNN-RNN chain to directly generate MPC commands, demonstrating a significant reduction in latency [32]. However, building and running the CNN-RNN chain adds computational overhead and acts as a “black box”, complicating the explainability and validation of decisions. In [30], an auto-encoder is used for EMG denoising, followed by adaptive backprop to adjust the parameters of an impedance controller [30]. One problem is that the auto-encoder for EMG denoising followed by adaptive backprop can overwrite the real signal behavior in the case of small data sets and can suffer from overfitting to noise.

These approaches have the advantage of being able to iteratively learn from feedback data to quickly compensate for spasmodic interference and signal perturbations, accelerating trajectory error convergence and significantly reducing latencies in command generation.

5. Bayesian learning for control

Research [33] proposes a Bayesian Learning NMPC, estimating nonlinear uncertainties online without an observer, improving the efficiency of hand joint control [33]. But these Bayesian Learning NMPC without an observer may suffer from high latency in online GP inference, affecting the real-time control rate. Calandra et al. [34] propose a GP-based iterative learning control that quantifies uncertainties and adapts the command for increased accuracy [34]. But GP-based iterative learning control requires storing and processing a significant amount of historical data, which increases the complexity and computational time. In [35], GP (Gaussian Process) regression is proposed to customize the admittance of the exoskeleton based on the confidence in the predictor [35], but GP regression for admittance customization critically depends on the choice of kernel and hyperparameter calibration, and unreliable predictions may lead to under- or over-assistance.

Bayesian learning for control has the ability to quantify and manage nonlinear uncertainties in real time, adapting control command for increased accuracy and robustness based on the confidence of Bayesian predictions.

These approaches contribute to improved control but require high quality and quantity of training data. Insufficient data can lead to overfitting and poor performance in new patients. Complex models provide predictions that are difficult for therapists to interpret, which complicates error diagnosis and clinical acceptance. The basic challenge is to combine the power and flexibility of intelligent algorithms with the strict requirements of safety, stability and explainability imposed by medical applications.

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3.3.2. Practical Applications in Rehabilitation

- Adjusting the level of support based on the patient's effort (automatic determination of passivity or voluntary activity);
- Automatic recognition of correct vs. incorrect movement patterns;
- Automatic personalization of exercises based on the patient's profile and their evolution over time;
- Real-time adaptation of robot trajectories based on EMG, EEG or sensory feedback data [18].

3.3.3. Advantages and Limitations for Intelligent Algorithms and Machine Learning

Advantages:

– High level of customization;

– The possibility of learning from clinical experience and individual patient behavior;

– High potential for automation and scalability.

Limitations:

– Requires large volumes of data for training;

– Performance depends on the quality of sensors and data;

– The explainability of decisions can often be low ("black-box" AI);

– Real-time integration can be difficult without high-performance hardware.

3.4. Predictive Control (MPC)

Predictive control is a model-based control (MPC – Model Predictive Control). It is an advanced control method that uses a mathematical model of the system to predict future behavior and optimize control actions according to a predetermined criterion. MPC predicts future states of the system over a time horizon and determines an optimal sequence of control commands so as to minimize a cost function. Only the first command in this sequence is applied to the system, after which the process is repeated at each time step.

Model Predictive Control (MPC) has become a central technology for optimal movement planning, with the ability to simultaneously manage constraints imposed by patient conditions. Several approaches to predictive control (MPC) have been studied:

1. MPC based on EMG signals.

Hsiao et al. [36] integrate EMG from calf muscles into the prediction horizon to adjust the torque applied to the knee joints [36]. However, integrating EMG into the prediction horizon increases the computational complexity and latency in optimizing the MPC, affecting the frequency of the control loop. In [37], EMG from the arm is used to generate trajectory and force references, reducing the tracking error [37], but the dependence on the quality of the arm EMG signal and its preprocessing can introduce estimation errors and require frequent calibration. In [38], EMG and plantar pressure sensors are combined for dynamic adjustment of weight bearing during walking [38]. The problem is that the fusion of EMG signals with plantar pressure sensors requires precise synchronization and can be sensitive to gait artifacts, affecting the stability of weight bearing adjustment.

The advantages of these studies lie in anticipating muscle intent through EMG signals, allowing the MPC to proactively adjust torque and load distribution, which leads to more accurate trajectory tracking, a more natural gait, and increased patient comfort.

2. Nonlinear MPC with Bayesian learning.

The paper [39] estimates the nonlinear terms online with a Gaussian Process and controls the discrepancies without the need for an observer. It has the advantage of online adaptation to uncertainties, improving the robustness of the predictive loop but has a high computational cost due to the real-time GP inference and the performance depends strongly on the choice and setting of the kernel [39]. In [40], NMPC is extended with iterative learning based on a GP (Gaussian Process) to improve the accuracy of the trajectories. Iterative learning refines the GP predictions and reduces the trajectory errors on each cycle but requires multiple training cycles for convergence, which prolongs the initialization phase. [40]. In the research [41], the admittance of the exoskeleton is adjusted depending on the confidence of the Bayesian predictions. This approach reduces the risk of patient overload when uncertainty is high, but calibration of confidence thresholds can be difficult and subjective, and GP inference adds additional latency to the loop, affecting the control frequency [41].

3. Deep learning-enhanced MPC.

Li et al. [42] propose a deep network for modeling dynamics and predicting system parameters, then integrating these predictions into a robust MPC. It improves the accuracy of the internal model of the MPC, especially in nonlinear systems, and allows online estimation of various parameters, increasing the robustness of the control but requires large amounts of data for initial training [42]. In [43], a DRL (Deep Reinforcement Learning) is used that includes an internal MPC that uses neural networks to optimize the prediction horizon. It combines the advantages of experience learning (DRL) with the stability of the MPC and the optimization of the prediction horizon is done adaptively, improving the trajectories. However, it has high complexity and high computational cost. [43]. The article [44] proposes a CNN-RNN chain that directly teaches the MPC commands for smooth and fast movements, but it is sensitive to noise in the input data, requiring robust preprocessing [44].

4. Hybrid MPC + adaptive.

In [45], MPC is combined with an adaptive gain control layer, reducing response times in gait systems. It combines the accuracy of MPC with the flexibility of online adaptation, but requires careful calibration of the interaction between the two layers and increases the complexity of the control algorithm [45]. In [46], adaptive admittance based on EMG is integrated into the MPC loop. It has the advantage of personalizing the level of assistance according to muscle effort and increasing the active involvement of the patient, but it strongly depends on the quality of the EMG signal. In [47], a hybrid MPC is used that alternates between passive and active modes according to the EMG signal. It allows smooth transitions between therapy modes according to the patient's condition and optimizes the level of assistance in real time, but it poses the risk of unstable switching if the EMG signal is ambiguous or noisy.

The biggest challenge of adaptive control is the dependence on a precise model, modeling errors reduce the accuracy of predictions and can lead to suboptimal or unstable controls. Solving the optimization on the prediction horizon at each control step can require significant computational resources which can induce latency and therefore prevent real-time response. The use of EMG in the prediction horizon adds an additional level of variability and delay that must be modeled or compensated for in the MPC.

3.4.1. Rehabilitation Applications

MPC is used in:

- Exoskeletons that must coordinate the movements of the patient's multiple joints;
- Systems that impose safety limits (e.g. avoiding hyperextension);
- Control of the contact force between the patient's limb and the robot [25].

3.4.2. Advantages and Limitations for Predictive Control Algorithms

Advantages:

– Can simultaneously manage physical constraints (e.g. position, speed, force limits);
– Allows planning of movements and their adaptation in real time;
– Integrates complex biomechanical models, useful in personalized rehabilitation.

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Limitations:

- It requires an accurate mathematical model of the system and the interaction with the patient;
- High computational cost – may require high-performance hardware or optimizations;
- Performance depends on the accuracy of predictions.

3.5. Robust Control

Robust control is designed to maintain the desired system performance despite model uncertainties or external disturbances. It is useful in applications where the variations cannot be completely modeled, but their limits are known.

Managing uncertainties and external disturbances is essential for patient safety, and robust control strategies are developed for exactly this purpose. Robust control approaches:

1. Sliding Mode Control

Lee et al. [48] demonstrated that the use of robust methods, such as sliding mode control, can maintain the stability of the interaction even in the presence of significant variations, noting that robust methods can compensate for external disturbances without compromising safety but can introduce "chattering" if not properly filtered, affecting comfort and requiring careful design of the sliding surface for each biomechanical segment [48]. The authors of the article [49] implemented a model-free adaptive sliding-mode control on a lower limb exoskeleton, demonstrating a fast convergence rate and robustness to uncertainties. Due to the fact that it does not require knowledge of the plant model, it is facilitated to implement on various prototypes, but in the absence of a model, the adaptive tuning can become empirical and dependent on experimental data and the complexity of the adaptive law can increase the computational cost [49]. In [50] sliding mode is combined with a perturbation observer to ensure accurate compensation of dynamic variations in elbow rehabilitation. The observer reduces the need for very large gains, but its integration adds latency and implementation complexity [50].

As a general conclusion, Sliding Mode Control offers excellent robustness and fast convergence in the presence of uncertainties, but it can induce chattering and requires careful tuning and filtering to ensure comfort and stability.

2. Control H∞H_\inftyH∞.

Zhang et al. [51] argue that H∞H_\inftyH∞ control increases tolerance to modeling errors and improves performance in systems with large uncertainties, but the design of the H∞ controller can be conservative, reducing performance under nominal conditions [51]. The authors [52] applied a H∞H_\inftyH∞ controller on a knee rehabilitation robot, demonstrating a 30% reduction in trajectory deviation in the face of unexpected perturbations, but requiring the solution of complex optimizations, which impose computational cost and implementation difficulties [52]. In [53], H∞H_\inftyH∞ was compared with PID and LQR in the control of an arm exoskeleton, showing that H∞H_\inftyH∞ offers the best performance under clinically variable conditions, outperforming PID and LQR in stability and tracking, but the design and tuning of H∞ are much more laborious and require advanced expertise in robust control. [53].

Robust control strategies aim to guarantee stability and performance in the presence of uncertainties but assume a known set of perturbations and uncertain patterns. In clinical practice, the types of unpredictable patient behaviors can be much more diverse than those included in the model, which can reduce the efficiency of the robust scheme. To cushion the perturbations, robust control can generate clumsy movements, slower response, diminishing the feeling of fluidity and naturalness of the exercises.

3.5.1. Rehabilitation Applications

Robust control is applicable in scenarios where the patient has unpredictable movements or passive limb resistance is difficult to estimate, while maintaining the safety of the therapy.

3.5.2. Advantages and Limitations for Robust Control Algorithms

Advantages:

– Guaranteed stability under uncertain conditions;
– Increased tolerance to modeling errors;
– Reliable in clinical applications where safety is essential.

Limitations:

– It can induce noisy behaviors if not properly filtered;
– The complexity of implementation is higher than classic control.

3.6. Hybrid Control

Hybrid control is a complex approach that combines multiple control types – such as positional control, force control, and adaptive or intelligent methods – to manage variable interactions between the robot and the patient. These systems combine the advantages of adaptive, predictive, and robust methods so that they can react to both real-time variations and uncertainties in the operational environment. This method is particularly useful in the context of rehabilitation, where a smooth transition between the patient's passive and active states is essential [54].

Various hybrid control techniques have been studied, such as:

1. "Virtual Fixture" technique.

Onfianii et al. [55] combined MPC and robust control in a Virtual Fixture scheme for upper limb rehabilitation, allowing smooth switching between passive and active modes by combining MPC prediction with $H\infty$ robustness for adaptive assistance, but the integration of the two control schemes is of high complexity and involves significant computational cost [55]. In [56] the authors introduced a variant that activates the fixtures only at major deviations, increasing patient-robot cooperation and avoiding unnecessary overload, but there is a risk of delayed reaction if the thresholds are not calibrated correctly. [56]. In the article [57] the Virtual Fixture was customized based on the biomechanical parameters of each patient, demonstrating significant increases in comfort and safety, but this requires detailed biomechanical measurements and preprocessing, increasing the setup time before therapy [57].

In conclusion, Virtual Fixtures offer guided assistance and smooth switching between modes, increasing safety and patient-robot cooperation, but comes with increased implementation complexity and the need for precise calibration of virtual parameters.

2. Human intent detection + active control.

The work [58] used a Bayesian classifier for EMG, which instantly triggers the switch to the active mode, ensuring the correctness of the exercises but the performance depends on the quality of the classifier and can be affected by EMG noise. Wu et al. [59] combined a neural network intention prediction module with a hybrid predictive control, reporting a 22% reduction in response delay but implying increased architectural complexity and high computational cost due to the neural network and predictive optimization [59]. In [60] the authors integrated EEG and EMG in a hybrid scheme, where multiple sources of intention trigger distinct assistance commands. Multimodal fusion improves decision accuracy and provides more precise assistance but requires complex equipment and rigorous synchronization between EEG and EMG signals [60].

In conclusion, by combining human intention detection with active control, systems achieve a fast and precise response to user intentions, improving the accuracy of exercises, but it involves increased complexity and dependence on the quality of multimodal sensors.

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3. Dual-modal control (adaptive + load-based)

In [61] the authors integrated adaptive admittance and a task-based module for grasping exercises, demonstrating an 18% improvement in trajectory accuracy, but the synchronization and coordination of the two modules is required, which can introduce latency and additional integration complexity [61]. In [62] the authors combined EMG-based adaptive control with a module that recognizes the type of task and automatically selects the optimal gain profile. This approach requires robust task classification and can be sensitive to recognition errors, affecting the stability of the chosen gains [62].

Dual-modal control flexibly combines adaptive with task-specific, increasing precision and personalization, but requires careful integration and depends on accurate task detection to avoid latencies or selection errors.

4. Adaptive active-passive switching

The study [63] proposes a parametric control that automatically alternates between passive and active impedance, based on force measurements, but in this case the calibration of force thresholds is critical because inappropriate thresholds can trigger premature or delayed switching [63]. In [64] a multimodal system with EMG and force sensors was demonstrated, which changes the assistance mode without perceptible interruptions improving patient comfort but it is worth noting the dependence on precise signal synchronization and EMG quality, as artifacts can cause erroneous switching [64]. Landi et al. [65] introduced a dual scheme that rapidly adjusts hydraulic gains in exoskeletons, allowing smooth transitions between modes based on muscle effort thresholds, but the complex hydraulic mechanisms and fast control may require specialized hardware and high maintenance [65].

Despite the advantages of hybrid control, it requires architectural and integration complexity. The synergy of two or more control loops significantly increases the complexity of the hardware and software and requires their good synchronization. Large processing resources are required for real-time inference and minimizing latency. Calibrating multiple parameters for safe and efficient interaction requires elaborate identification and testing procedures. Hybrid strategies involve additional sensors, more powerful processors, and more complex software development, which can increase the total system cost and maintenance difficulties.

3.6.1. Application Examples

- Robots with automatic mode switching: Exoskeletons that use EMG data to switch between passive and active modes, depending on detected muscle effort [66].
- Multimodal feedback rehabilitation systems: Integrate visual, auditory, and haptic feedback, combined with hybrid control to support motor learning and patient engagement [67].

Integrating multiple strategies:

In hybrid control systems, each method contributes a distinct set of benefits:

- Adaptive methods allow for continuous adjustment of control parameters, responding quickly to individual patient variations.
- Predictive algorithms anticipate the future evolution of the system and optimize movement trajectories to respect the constraints imposed by clinical conditions [68], [69].
- Robust techniques ensure system stability in the face of external disturbances and modeling uncertainties, ensuring operational safety [70], [71].

3.6.2. Advantages and Limitations for Hybrid Control Algorithms

Advantages:

– High flexibility in the face of variations in patient behavior;
– Real-time adaptability;
– Allows a more natural interaction between patient and robot.

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Limitations:

- High complexity in design and implementation;
- The need for precise synchronization between sensors and algorithms;
- Higher costs due to hardware and software requirements.
- Implementing a hybrid control imposes high processing requirements, careful integration of feedback from multiple sources (from position sensors, force, EMG, etc.) and requires precise parameter calibration.

The major challenge remains the uncompromising integration of these technologies into clinical environments, where every aspect of the interaction must be monitored and adjusted in real time [72], [70].

Table 1. Advantages and limitations of control algorithms in robotic rehabilitation.

Algorithm	Advantages	Limitation
PID	- Simple implementation - Fast response in linear systems - Easy to adjust	- Does not adapt to dynamic variations - Unstable in nonlinear or delayed systems - Does not learn from previous behaviors
LQR	- Optimal balance between accuracy and consumption - Efficient in well-designed systems	- Requires precise model - Sensitive to uncertainties - Difficult to apply to patients with unpredictable responses
Adaptive control	- Responds dynamically to changes - Personalizes therapy - Increases safety	- Requires precise sensors and high processing - Risk of instability without proper calibration
Intelligent control / AI	- High level of customization - Learning from experience - Automation and scalability	- Requires a lot of data - Performance depends on sensors - "Black box" difficult to explain - Real-time integration can be difficult
Predictive control (MPC)	- Manages multiple constraints - Real-time planning and adaptation - Integrates biomechanical models	- Requires accurate model - High computational cost - Performance depends on the accuracy of predictions
Robust control	- Stability under uncertain conditions - Tolerance to modeling errors - Increased safety in clinical applications	- Can generate noisy movements - Complex implementation compared to classic methods
Hybrid control	- Flexibility to patient variations - Real-time adaptability - Natural patient–robot interaction	- Complex design and implementation - Requires precise synchronization - High hardware/software costs

4. Challenges and Limitations in Implementing Control Algorithms

Although the development of control algorithms for medical recovery robots has advanced significantly, there are numerous challenges that influence both the efficiency of the systems and their clinical applicability.

4.1. Variability of Patient Response

One of the biggest challenges is adapting in real time to the unpredictable and variable behavior of the patient. Differences in muscle tone, motivation level, pain or joint stiffness require increased control flexibility, which is difficult to provide with classical methods. Adaptive control and machine learning techniques have proven useful in this regard, but they involve challenges in terms of stability and convergence speed [73].

4.2. Accurate Modeling of the Patient-Robot System

Biomechanical models of patient-robot interaction are often simplified to reduce the complexity of real-time computation, which can lead to reduced control accuracy. For example, in [74], the authors point out that kinetodynamic models for upper limbs integrated with robotic exoskeletons can vary significantly depending on the patient's morphology. This variability requires the development of control algorithms that are robust to uncertainties.

4.3. Patient Safety

In the case of recovery robots, safety is essential. Systems must prevent the application of excessive forces or unwanted movements, which limits the freedom of control design. In [75], it was shown that integrating haptic feedback and dynamic limits into predictive control can significantly increase safety, but at the cost of increased implementation complexity.

4.4. Lack of Standardization and Difficulties in Clinical Integration

Another major obstacle is the lack of standardization between robotic platforms and the lack of interoperability with existing clinical systems. In addition, most systems are designed for testing protocols in controlled environments, not for daily use in clinics. The study by [76] shows that clinical adoption is often delayed due to difficulties in integrating robotic systems into the therapeutic flow.

4.5. High Costs and Maintenance

Advanced robotic systems require high-precision sensors, powerful processors, and sophisticated mechanisms, which lead to high acquisition and maintenance costs, limiting their spread to smaller clinics or resource-poor regions [77].

In conclusion, despite notable progress in the development of control algorithms for medical rehabilitation robots, their implementation in clinical practice remains a complex challenge. Limitations related to patient variability, modeling complexity, operational safety, integration with existing systems, and high costs continue to hinder widespread adoption. Modern approaches, such as adaptive, predictive, or hybrid control, offer promising perspectives, but require further optimization and validation to meet the real needs of patients and therapists. Therefore, a close collaboration between researchers, clinicians, and engineers is essential to overcome these obstacles and transform these technologies into an accessible and effective therapeutic standard.

5. Future Directions of Research and Innovation

The development of control algorithms for medical recovery robots is a continuously evolving field, and its future is closely linked to integration with emerging technologies, personalization of treatment, and increasing the level of autonomous intelligence of systems.

One of the main directions aims at integrating machine learning and artificial intelligence (AI) to optimize therapy in real time. Reinforcement learning algorithms are increasingly used to adapt control strategies according to individual patient responses. A relevant example is the work of Li et al. (2021), who proposes an Actor-Critic algorithm for controlling an exoskeleton intended for upper limb rehabilitation, achieving efficient adaptation to patient needs [77].

There is also growing interest in integrating augmented reality (AR) and virtual reality (VR), which allow for more intuitive and motivating interaction during exercise. In a recent study published in Sensors (2022), researchers combined a robotic exoskeleton with an interactive VR environment to provide real-time visual and auditory feedback, improving patient engagement [78].

Collaborative control algorithms that enable safe human-robot interaction are becoming a priority as therapists seek to retain some degree of human involvement. Haptic feedback control, with dynamic adjustments of force and trajectory, is in full development. For example, Zhang et al. (2020) proposed a hybrid force- and position-based control strategy that reduces patient discomfort during passive therapy [79].

In the long term, a transition towards fully autonomous systems that can assess, plan and execute personalized therapies without direct human intervention is anticipated. This requires the development of algorithms with a high degree of robustness, capable of handling significant biomechanical and behavioral variations.

Other promising directions include:

- Using wearable sensors and IoT for continuous monitoring of patient progress;
- Using digital twins to simulate and test control strategies before their clinical application;
- Control based on multimodal data (movement, EMG, EEG), for a holistic understanding of the patient's condition and intelligent adaptation of therapy.

In conclusion, progress in this field will depend on the ability to combine intelligent algorithms with intuitive interfaces and reliable hardware, in a clinically accessible and effective way.

6. Conclusions

The use of robots in assisted medical rehabilitation represents one of the most promising directions of development in the field of neuromotor rehabilitation. These robots allow not only the precise and repetitive execution of therapeutic exercises, but also the detailed monitoring of patients' performance and dynamic adjustment of therapy. At the heart of this capability are control algorithms, which play a crucial role in the way robots interact with human users.

This paper presented a detailed analysis of the main types of algorithms used in this context: from classical ones (such as PID control), to advanced methods (adaptive, predictive, robust or hybrid control), as well as recent trends in the integration of artificial intelligence and machine learning. Recent studies highlight the shift from rigid and predefined schemes to adaptive and intelligent solutions, capable of personalizing therapy in real time and improving clinical outcomes [80], [81].

At the same time, we have identified a number of persistent challenges, including the biomechanical complexity of human-robot interaction, interindividual patient variations, safety requirements, and associated costs. However, the rapid progress of related technologies, such as advanced sensing, virtual reality, and deep learning, opens new perspectives for the development of more performant and clinically accessible control systems [82].

Future research directions will focus on increasing the degree of autonomy of robots, improving human-machine interfaces and integrating a larger volume of data from various biometric sources. The ultimate goal remains to maximize the efficiency of therapy and increase the quality of life of patients, through solutions that combine technological performance with the empathy necessary in rehabilitation processes.

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