Rehabilitation Robotics: Current State, Technologies, and Future Directions

Syuzanna Matevosyan, *Department of Electrical and Computer Engineering, University of Patras, Greece*

***Abstract*— Sensorimotor impairments have significant effects on functional capabilities of individuals. At present traditional rehabilitation faces challenges to restore and rehabilitate these functions. Rehabilitation robotics presents an innovative solution to overcome those challenges and address the need worldwide. This report examines the transformative role of rehabilitation robotics in modern healthcare, focusing on its development, technical architecture, and control systems. The discussion leverages the evolution of rehabilitation robotics from its origins to today's advanced AI-integrated platforms, with particular emphasis on control mechanism of the robotics.**

***Index Terms*— Rehabilitation robotics, Therapeutic Robotics, Manipulation Aids, Intelligent Mobility Aids, Control Systems**

I. Introduction

THE global prevalence of motor disabilities continues to rise. Stroke alone affects approximately 1% of the global population [1]. After intensive rehabilitation, only 5-20% of stroke survivors achieve full functional recovery, with 25-74% remaining dependent on caregivers for basic tasks [2]. Additionally, demographic trends showing an aging population and increasing survival rates from traumatic injuries have created an urgent need for more effective, intensive rehabilitation solutions [3].

Rehabilitation robotics are a combination of robotics technology and rehabilitation science [4]. These systems are fundamentally changing how we approach physical therapy and assistance for individuals with motor impairments. In recent years, with technological advancements there is a shift from passive assistive devices to intelligent, active systems. Current systems are capable to provide targeted, data-driven rehabilitation interventions. The field encompasses various robotic systems designed to address different rehabilitation needs (Fig. 1).

Therapeutic Robots: Therapeutic robots are specialized medical devices that provide repetitive training for motor recovery [5]. These robots continuously monitor the patient's movements through sensors; adjust their assistance level based on performance. They also can provide real-time feedback to both patients and therapists. There are two main categories: end-effector devices and exoskeleton. End-effector robots interact with patients through a single point of contact, typically at the most distal part of the limb (e.g., upper or lower extremity) [6]. It allows for natural kinematic activation. Generally, there is a less complex mechanical structure compared to exoskeletons. Also, it adaptable, meaning can accommodate different patient sizes with minimal adjustment [7]. However, several disadvantages exist, such as less precise control over individual joint movements, the limit in isolating specific joint training, and the allowance of undesired movements [8, 9]. On the other hand, exoskeletons are wearable robots that align with the patient's joints and limb segments, providing direct support and guidance throughout the movement. They attach to multiple points along the limb; mechanical joints correspond to anatomical joints. Exoskeletons control specific joint movements independently and provide comprehensive support throughout the movement range. They require more complex setups and higher cost due to complex mechanical design [10].

Robotic Manipulation Aids: Robotic manipulation aids represent a major category in rehabilitation, designed to help individuals with limited upper limb function to perform activities of daily living (ADL) and vocational tasks. These devices are more commonly available and widely used compared to therapeutic robots [11]. Robotic manipulation aids directly address functional needs. For example, they help with daily activities such as reaching and grasping, feeding, writing, working, etc. Wheelchair-Mounted Systems is a hybrid

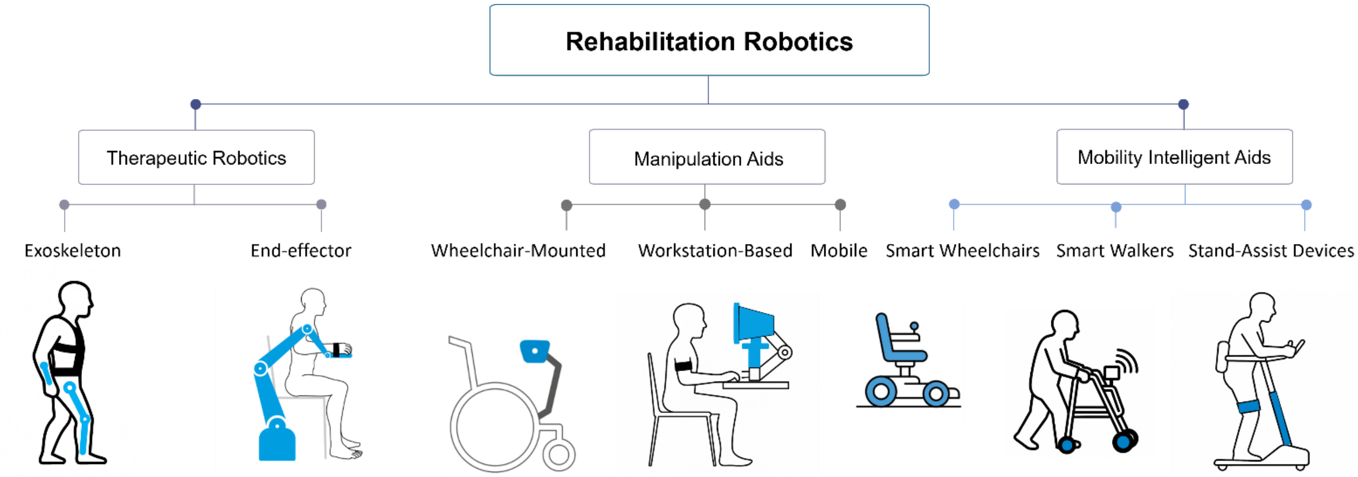

Fig. 1. Categories of robotic systems for different rehabilitation needs.

system that has "third arm" for it's users, offering the greatest flexibility and mobility. Robotics in this category typically have multiple degrees of freedom (often 6-7 DOF) and advanced end-effectors, allowing users to perform a wide range of tasks. Tasks evolve around picking up objects from the floor to operating doors and elevators. Their primary advantage is constant availability and ability to assist in various environments. Balance should preserve between functionality and weight considerations. Workstation-Based Systems are fixed installations designed for specific locations where certain tasks are regularly performed, such as offices, kitchens, or workshops. These systems typically offer more stability and precision than mobile solutions, making them ideal for repetitive tasks or detailed work. While limited in mobility, these systems can be more robust and often more cost-effective for their specific applications. And the last, Mobile/Standalone Systems, represent a flexible middle ground, designed to be moved between locations but not permanently mounted to a wheelchair or workstation. These might include portable robotic arms that can be positioned on different surfaces or dedicated feeding devices that can be used at various locations. These systems offer a balance between portability and functionality though they may require some setup time when relocating.

Intelligent Mobility Aids: (IMAs) have emerged to address limitations of traditional mobility devices, particularly for individuals who find it difficult or impossible to use standard mobility aids independently. These users often include people with low vision, visual field neglect, spasticity or tremors, cognitive deficits [12]. The core components of an IMA typically include sensors to understand the environment, control software to process data and make navigation decisions, input methods to control device and feedback system to provide information to the user about the environment and system status [13]. There are three types of intelligent mobility aids: smart wheelchairs, smart walkers and stand assist devices. Smart wheelchairs enhance traditional powered wheelchairs with intelligent features and autonomous capabilities. They represent one of the most researched and developed categories of IMAs [14]. Adaptive control systems allow modification of driving parameters based on the user capability and environment [15]. It enables independent mobility for users with severe motor or cognitive impairments. The second type, Smart walkers, is built upon traditional rollators by incorporating intelligent features to improve safety. Sensors are used to avoid obstacles. Third type, Stand-assist devices combine robotics and intelligent features to help users safely transition between sitting and standing positions. They continuously monitor user position and balance and provide smooth, controlled transitions between positions.

Regardless of the specific type, its therapeutic robots, manipulation aids, or intelligent mobility aids—a common challenge is the development of those systems [16]. Especially critical is the control mechanism, that should accurately model and respond to human kinematics and dynamics. While advancements have been made in hardware and sensor technology, a significant gap remains in creating control algorithms that can ensure natural, safe, and truly adaptive human-robot interaction [17]. This limitation is particularly evident in complex tasks like gait rehabilitation, where achieving human-like movement patterns is paramount for functional recovery, but it also impacts the precision and intuitiveness of manipulation and mobility aids [18].

This review paper aims to analyze control systems research gap. Starting from history, it will describe the current state of rehabilitation robotics with a particular focus on control strategies and integration of kinematics and dynamics. By identifying the limitations in existing approaches and exploring emerging solutions, this paper seeks to highlight pathways toward developing more effective control systems for the next generation of rehabilitation robots.

II. Historical Evolution of Rehabilitation Robotics Control System

A variety of promising control systems have been introduced for the rehabilitation robotics throughout history. The diverse approaches reveal an evolution from simple open-loop systems to sophisticated adaptive and interactive controls (Fig. 2).

A. Early Foundations: 1940s – 1960s

The concept of robotics, which would eventually influence rehabilitation applications, began to take shape in the 1940s. During this decade, science fiction author Isaac Asimov famously formulated his "Three Laws of Robotics,". While fictional, it provided an early ethical framework and sparked thought about human-robot interaction and safety [19].

Practical robotics can be traced back to early industrial applications like the DeVilbiss paint sprayer in the 1930s [20], and the Animation robot company was formed in the 1950s [21], setting the stage for more complex robotic systems

The earliest attempts in rehabilitation robotics were characterized by relatively simple control mechanisms, due to the limited computer technology and sensor capabilities.

One of the pioneers was CASE Institute of

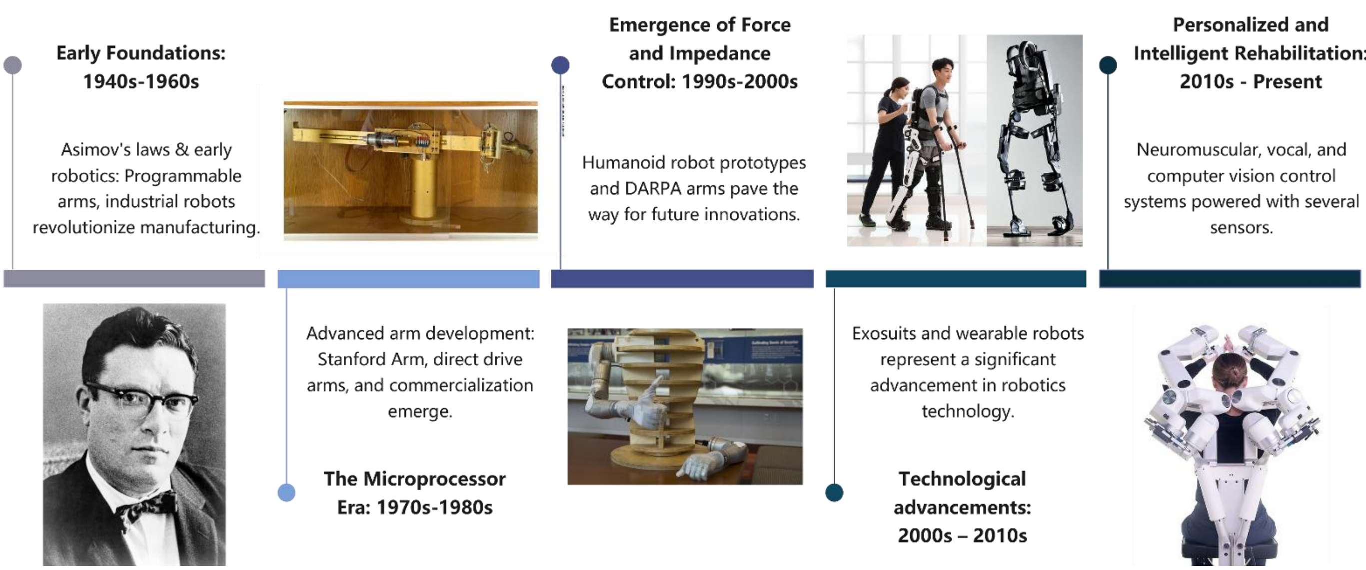

Fig. 2. History of rehabilitation robotics.

Technology, which introduced powered orthosis (early 1960s) [20]. These systems relied on pre-recorded manipulative tasks. This represents a form of open-loop control, where the robot executes a predefined sequence without real-time adaptation to the user's state or intent, beyond basic closed-loop position control via incremental encoders. Similarly, the Rancho Los Amigos "Golden Arm" (Fig. 3) utilized a joint-by-joint control method [22]. While electrically powered, this approach often proved unintuitive for users, as it required them to manage individual joint movements rather than performing coordinated, task-oriented motions. The control challenge in this era was fundamental: how to make a mechanical device perform a desired motion. The solutions were often direct extensions of industrial automation concepts, lacking the user-friendly approach. Kinematic compatibility was primitive, and dynamic interaction was not a primary consideration in control design.

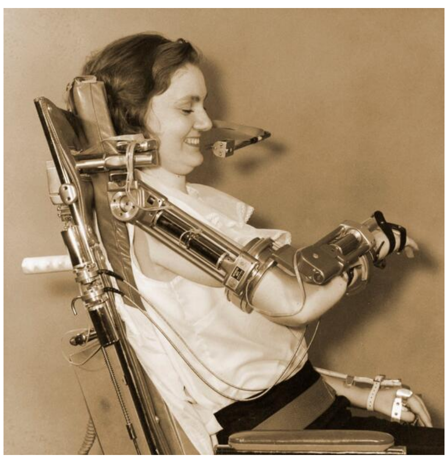

Fig. 3. The computer-controlled Rancho Arm is invented to help disabled patients at the California hospital Ranchos Los Amigos in 1963.

B. The Microprocessor Era: 1970s -1980s

Workstation-based systems like Roesler's design and the Johns Hopkins University system still relied on pre-programmed commands to manipulate objects [23]. However, the control logic could be more intricate. The Johns Hopkins system, for instance, required items to be in precisely known positions due to the arm's lack of sensors, underscoring a continued reliance on highly structured environments for successful open-loop or simple feedback control. User input mechanisms began to offer more continuous control. The Spartacus robot, for example, could be controlled by an analog input like a head-position-operated joystick. This represented a step towards more interactive control, though the underlying robotic actions were still largely pre-defined or directly mapped. The DeVAR systems from Stanford (Fig. 4) utilized standard industrial manipulators like the PUMA 260 [24]. While these arms had their own sophisticated internal controllers, their application in rehabilitation often involved higher-level supervisory control from a user or a program, focusing on task execution within a structured workspace.

During this period, control was predominantly position centric. The robot was commanded to go to a specific point or follow a path, with limited ability to modulate its force or adapt to unexpected user forces. This often led to rigid interactions, where the human had to adapt to the robot, rather than the other way around. Safety for high-power devices like Spartacus began to highlight the need for more responsive and inherently safer control strategies.

Fig. 4. The Stanford arm, on display at Stanford University

C. Emergence of Force and Impedance Control: 1990s – 2000s

This era marked a pivotal shift in control philosophy, moving from position control to strategies that managed the dynamic interaction between the robot and the user.

The limitations of purely position-controlled robots in rehabilitation became increasingly apparent. There was a growing need for robots that could safely interact with humans and provide compliant assistance. This eventually led research into force control and impedance/admittance control.

Impedance control, for instance, allows the robot to modulate its mechanical impedance (the relationship between force and velocity) as perceived by the user. This enabled robots to feel "softer" or "stiffer" as needed, facilitating more natural and safer physical human-robot interaction. The GENTLE/S project utilized a haptic arm in a virtual environment, where patients moved against resistance, relying on sophisticated force feedback and control [25] (Fig. 5, 6).

A key aspect of the GENTLE/S approach was its ability to provide resistance; patients would "move against a resisted haptic arm", particularly in its active therapy mode.

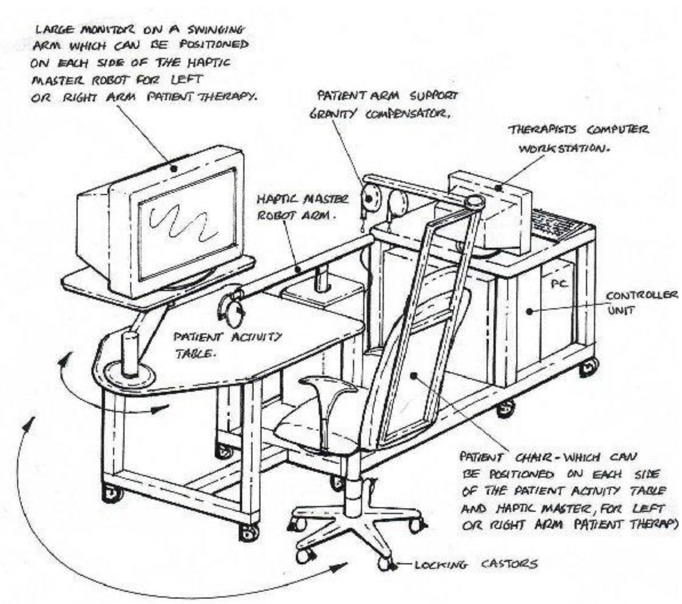

Fig. 6. Concept design sketch for the first rapid prototype of GENTLES/S project.

Active mode was similar to the active constrained mode found in other systems like MIME, where the patient actively moves against a force generated by the robot [26]. This interaction was underpinned by sophisticated force feedback capabilities inherent in the HapticMASTER, allowing for precise modulation of assistance and resistance based on the therapeutic goals.

MIT-Manus could operate in passive mode (robot moves the relaxed patient), active-assisted mode (patient initiates, robot assists along a path), or active-resisted mode (patient moves against robot-generated resistance) [27]. Moreover, this period saw the rise of "assist-as-needed" (AAN) paradigms. The control system's goal was to provide only the necessary amount of assistance to complete a task,

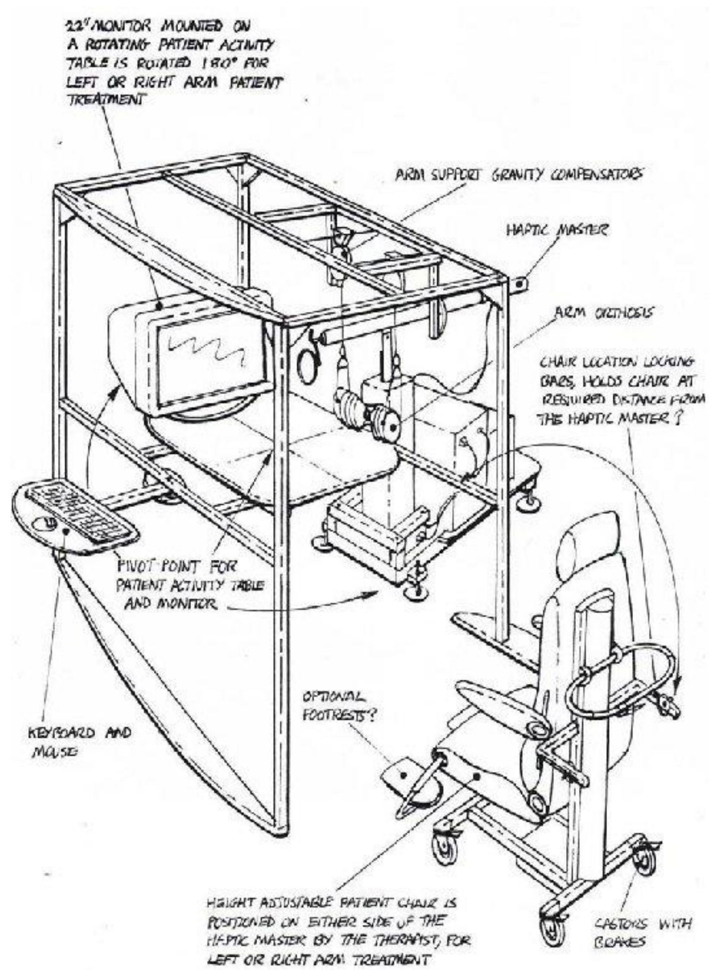

Fig. 6. Concept design sketch for the second rapid prototype of GENTLES/S project.

encouraging active participation from the patient. This required the robot to sense the user's contribution and adapt its own output accordingly.

E. Technological Advancements: 2000s – 2010s

The period from the 2000s to the 2010s marked a significant maturation and diversification in robotics rehabilitation. Driven by rapid technological advancements across multiple perspectives, this era saw growth in research publications, reflecting increased global interest and investment in the field. Improved sensor technology, including more accurate force/torque sensors, motion capture systems, and bio-signal detectors (like EMG and EEG for BCIs), became more integrated, providing richer data for control and assessment [28]. Actuator technology also improved, leading to robots that were more powerful, precise, and capable of rendering more nuanced forces and movements.

The 2000s and 2010s witnessed a remarkable surge in the development and application of exoskeletons and wearable robots in rehabilitation and assistive technology [29]. While foundational concepts existed earlier, this period saw these devices evolve from laboratory prototypes into more sophisticated, clinically relevant systems, and even some commercially available products aimed at restoring or augmenting human movement. These systems are defined as wearable robotic structures, often incorporating rigid and/or flexible components, designed to operate in close physical interaction with human limbs. Equipped with actuators, sensors, and increasingly complex control systems, they aimed to provide support, guidance, enhance motor function, or assist with daily activities.

F. Personalized and Intelligent Rehabilitation: 2010s - Present

The most recent phase has been characterized by the integration of learning, adaptation, and more intuitive human-robot interfaces into control systems. Adaptive control algorithms grow widely, allowing robots to personalize therapy. It includes several approaches such as impedance and its variants, Electromyography (EMG), Assist-as-Needed (ANN) controllers, Active Disturbance Rejection (ADRC), and other adaptive controls. This is crucial for optimizing the therapeutic challenge and maintaining engagement. Machine learning (ML) and Artificial Intelligence (AI) are increasingly used within control frameworks for tasks like user intent recognition, predicting movement, optimizing therapy parameters, and even adapting shared control strategies [30, 31, 32].

Novel control interfaces, such as EMG-based control (using muscle activity) and Brain-Computer Interfaces (BCIs), have emerged, offering more direct pathways for users with an intent to command the robot (Fig. 7).

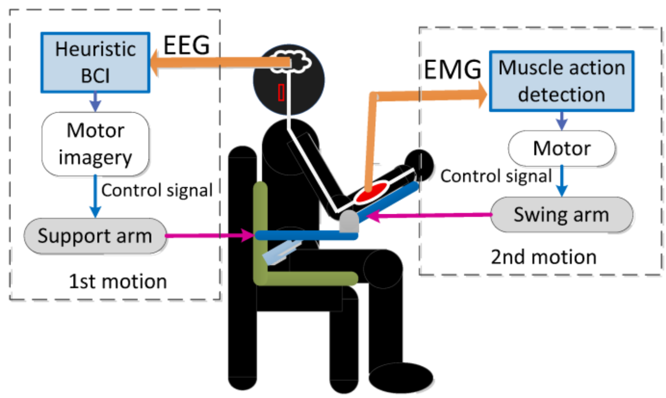

Fig. 7. Trial of Brain–Computer interface for continuous motion Using EEG and EMG

Shared control paradigms, where the human and the autonomous controller collaboratively manage the device, have matured. The control system must intelligently arbitrate or blend inputs from humans and its own autonomous functions (e.g., obstacle avoidance, path correction). Commercial systems like the Lokomat evolved to incorporate more adaptive control. This allows greater patient participation by reducing torque or applying impedance control to guide the patient's legs while allowing free walking within certain boundaries.

The integration of Virtual Reality (VR) with robotic therapy also places new demands on control systems. [33]. This requires tight synchronization between physical robot movements and the visual feedback presented to the user. VR-based systems often involve haptic rendering of virtual forces additionally [34].

TABLE I

[1] CURRENT TECHNOLOGIES IN PERSONALIZED AND INTELLIGENT REHABILITATION (2010S - PRESENT)

[1]

Technology Name	Body Part	Category	Purpose	Control System
Lokomat (Pro/Nanos)	Lower Limb	Therapeutic	Gait rehabilitation, Improve walking ability	Adaptive, Impedance, AAN, Force/Position feedback
ReWalk	Lower Limb	Therapeutic, Assistive (Mobility Aid)	Overground walking, Daily mobility assistance	User-initiated (CoG shift), Pre-defined patterns
EksoNR (Ekso Bionics)	Lower Limb	Therapeutic	Gait training, Neurorehabilitation	Adaptive (SmartAssist), User-triggered, AAN
HAL (Hybrid Assistive Limb)	Lower Limb, Full Body	Therapeutic, Assistive	Gait support, Movement augmentation, ADL assist	EMG-based (Bio-cybernic), (Research: BCI)
ArmeoPower	Upper Limb	Therapeutic	Arm/shoulder motor recovery, Intensive therapy	Adaptive, AAN, Force/Position feedback, VR integration
ArmeoSpring	Upper Limb	Therapeutic	Arm/shoulder therapy, Active movement support	Weight support, Sensor-based feedback
InMotion ARM/HAND (BIONIK)	Upper Limb / Hand	Therapeutic	Stroke recovery, Motor skill retraining	Impedance, AAN, Force feedback, Performance tracking
Kinova JACO / Gen3	Upper Limb (Arm)	Manipulation Aid (Assistive)	ADL assistance, Object manipulation	Joystick, Shared Control, (Research: EMG, BCI, AI)
REX Exoskeleton	Lower Limb	Therapeutic	Balance & lower limb function (stroke rehab)	Pre-set movements, Repetitive training
HandSOME (Robotic Glove)	Hand	Therapeutic	Hand dexterity, Fine motor skill recovery	Sensor-based, (Often with VR)
Nao (SoftBank Robotics)	Humanoid (Whole Body)	Social/Cognitive Support (Assistive)	Social interaction, Motivation, Cognitive exercise	AI, NLP, Emotion recognition, Interactive programming
Pepper (SoftBank Robotics)	Humanoid (Whole Body)	Social/Cognitive Support (Assistive)	Social engagement, Information, Assistance	AI, NLP, Touch sensors, Autonomous navigation (limited)
BCI-Integrated Systems (Research Focus)	Varies (Prosthetics, Robots)	Assistive, Therapeutic	Direct neural control for severe paralysis, Neurofeedback	BCI (EEG, ECoG), ML/AI decoding, Shared Control

In summary, the historical trajectory of control in rehabilitation robotics shows a clear progression from rigid, pre-programmed machines to highly interactive, adaptive, and increasingly intelligent systems. The ongoing challenge remains to develop control systems that can seamlessly and effectively manage the complex kinematic and dynamic interactions inherent in human movement, thereby maximizing the therapeutic potential of these technologies.

III. Therapeutic Robotics

Therapeutic robotics represents a significant advancement in rehabilitation medicine. The goal is assisting patients to recover lost motor skills and enhance functionality following neurological injuries [5]. Stroke, spinal cord injury, or other conditions lead to such impairments. The core purpose of these robots is to automate and augment traditional therapy, providing intensive, repetitive, and task-specific training that is crucial for neuroplasticity and motor relearning. Unlike purely assistive robots designed for long-term daily support, therapeutic robots are typically used for a defined period within a rehabilitation program. They are designed to facilitate exercises for upper limbs, lower limbs, or even specific joints, often by guiding movements, providing controlled resistance or assistance, and offering precise feedback on performance. By enabling longer, more consistent, and potentially more engaging therapy sessions, these systems aim to optimize the recovery process, improve patient outcomes, and sometimes reduce the physical burden on human therapists.

IV. Control Systems in Therapeutic Robotics

Control systems in therapeutic robotics are crucial for assisting in physical therapy, replacing lost motor functions, or facilitating emotional and social interaction. These systems interpret user intent or pre-programmed routines to guide robotic actions safely and effectively.

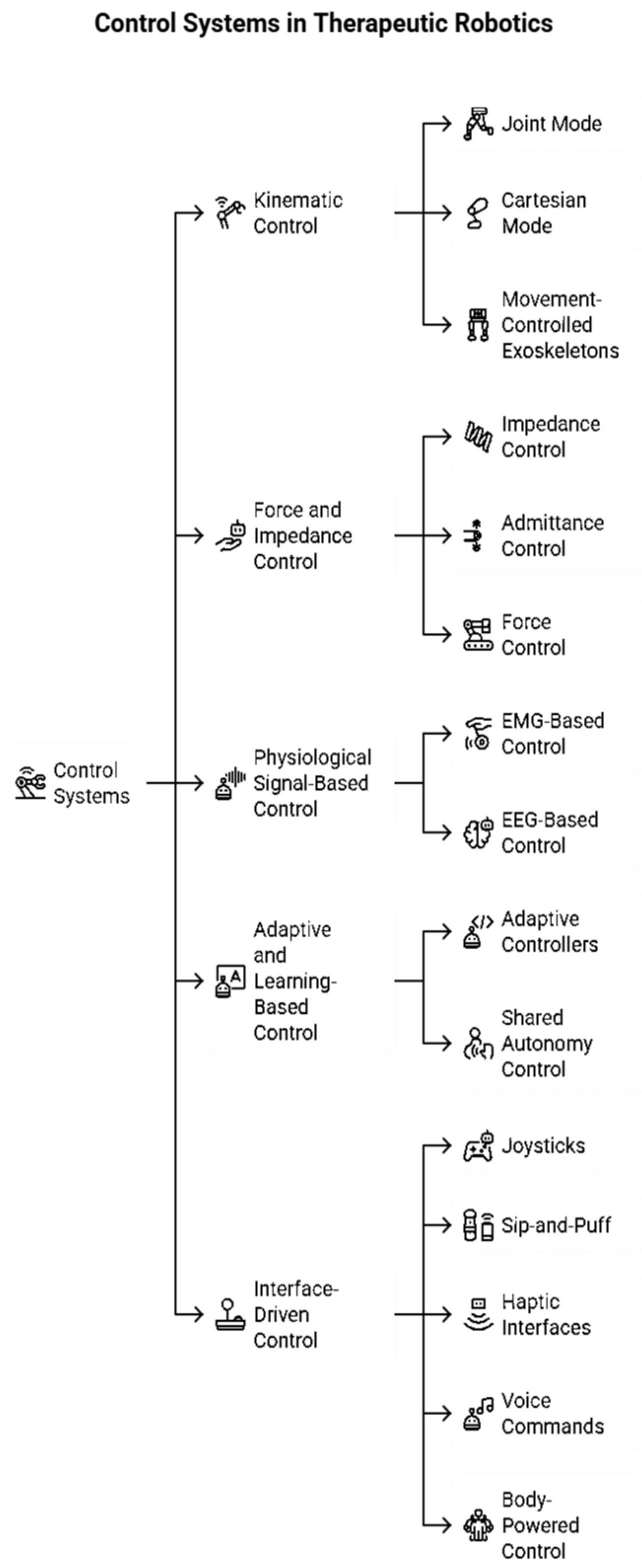

Fig. 8. Overview of control systems in therapeutic robotics

A. Kinematic Control (Position and Movement-Based)

This category focuses on controlling the robot's position, orientation, and movement in space. There are several types of kinematics control such as joint mode, cartesian mode, and movement-controlled exoskeletons. In joint mode (Joint-by-Joint Control) each joint of the robotic arm or exoskeleton is controlled individually [35]. While it is easier to implement, this mode often requires the user to constantly adjust multiple joints to achieve precise end-effector positioning. The Rancho Los Amigos "Golden Arm" (Fig. 3) utilized a form of joint-by-joint control.

The cartesian mode control system manages the position and orientation of the robot's end-effector (e.g., hand, footplate) in a Cartesian coordinate system (X, Y, Z) [36]. This requires inverse kinematics to calculate the necessary joint angles to reach the desired pose (Fig. 9). Position control is a common strategy where therapists define trajectories for the patient to follow. Devices like the AutoAmbulator (ReoAmbulator) and Virtual Gait Rehabilitation Robot (ViGRR) use position control via a Human-Machine Interface (HMI) [37].

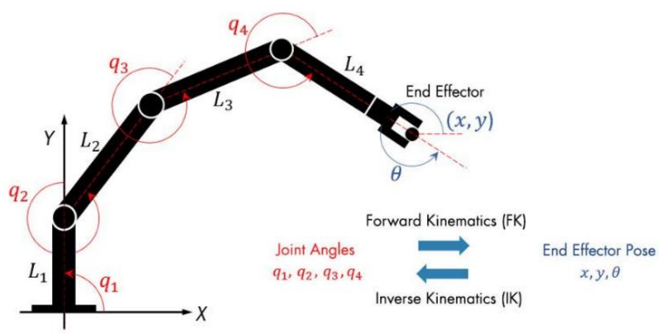

Fig. 9. 4-joint robotic manipulator with links L_1 to L_4 and corresponding joint angles q_1 to q_4. The end effector's position is represented by coordinates (x, y) and orientation θ. It shows the relationship between joint angles (input for forward kinematics) and end-effector pose (input for inverse kinematics), highlighting the bidirectional mapping between them.

The movement-controlled exoskeleton uses information derived from the user's motor execution to send control signals to the exoskeleton. For example, an upper-limb exoskeleton designed for tremor suppression measures limb motion with inertial measurement units (IMUs) to determine the tremor's amplitude and frequency, then applies a canceling force [38]. Gait phase detection, which identifies different stages of walking (e.g., heel strike, swing phase) using footswitches or IMUs, is another form of movement-based control used to apply forces appropriately. The P.REX exoskeleton, for instance, uses a combination of footswitches and IMUs for gait phase detection to provide varying levels of assistance [39].

B. Force and Impedance Control

Force and impedance control systems regulate the interaction between the robot and the user, leading to more natural interactions. The main relationships established between position and force, where the robot behaves like a programmable spring-damper system. It accepts position or velocity as input and outputs force or torque. Impedance control is frequently studied and allows for safer and more comfortable physical human-robot interaction. The Lokomat, after initial passive exercises, implements impedance control to allow patients to walk more freely. It is done by repositioning their legs to the initial trajectory if they deviate [40]. The Pedianklebot and Inmotion2 also utilize impedance control [41, 42]. Anklebot uses adaptive impedance control, where parameters are gradually modified based on patient progress [43]. Physiotherabot implements impedance control for position and force in gait rehabilitation for various conditions [44]. A knee rehabilitation device designed by Akdogan et al. uses impedance control adjusted by rules based on the patient's external force [45].

Admittance control is the opposite of impedance control, where force or torque are input, and velocity or position are outputs. Admittance control can be used for speed regulation based on patient-device interaction.

Force control strategy directly controls the forces exerted by the robot. It's often used in conjunction with position control to manage patient interaction forces during therapy.

C. Physiological Signal-Based Control

These systems use biological signals from the user to infer intent and control the robot. Electromyography (EMG) Based Control (Neural-Controlled/Myoelectric): EMG signals, which measure the electrical activity produced by muscle

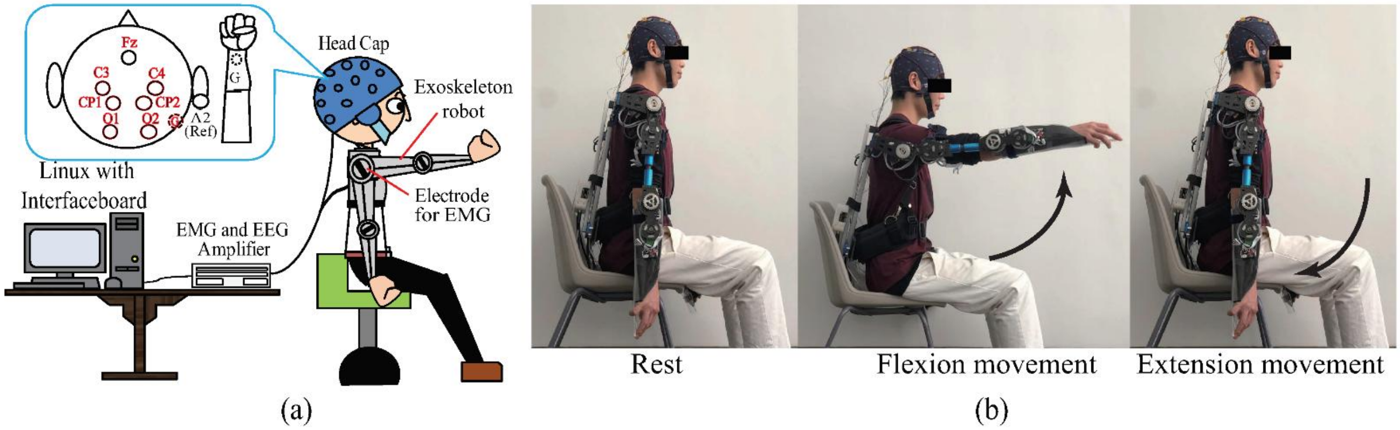

Fig. 10. EEG and EMG signals control an upper-limb exoskeleton robot. (a) electrodes, amplifiers, and a Linux interface (b) subject performing rest, arm flexion, and extension.

activation, are widely used [46]. These signals, detected by sensors placed on the skin (surface EMG) or implanted within the muscle (intramuscular EMG), represent the electrical activity associated with muscle contractions [47]. Surface EMG (sEMG) is non-invasive and can detect movement intent even if the muscle activity is insufficient to move a joint (Fig. 10).

Direct Control: Direct control (also called amplitude or threshold modulation control) is the simplest method in EMG control mechanism. It uses the amplitude of EMG signals from one or two muscle sites—typically antagonistic pairs such as flexors and extensors—to activate corresponding robotics function [48]. For example, contracting the wrist flexor muscles opens the robotic hand, while contracting the extensors closes it. Some devices allow proportional control, where the strength of muscle contraction determines the speed or force of movement. This control requires repeated practice from users to master the selective contraction of residual muscles. In these systems a pair of EMG electrodes typically control a single degree of freedom (DoF) [49].

Pattern Recognition: Pattern Recognition is an advanced control strategy using multichannel EMG data and machine learning. PR systems decode EMG patterns to recognize complex user intentions like grasp types or simultaneous movements [48]. Subsequently, this gives a greater degree of freedom and intuitive control (Fig 11). When using advanced rehabilitation robotics, a user needs to generate distinctive and repeatable muscle activation patterns [49]. For accurate control, signals should be recognized by the classifier embedded within the robotic device. Machine learning techniques map signals from an array of EMG electrodes to a set of movement classes, allowing control over more DoF.

EMG signals can be used as feedback for the robot's controller, allowing the device to adjust assistance levels based on the patient's muscle activation. Adaptive control with EMG signals anticipates the patient's intention to move. The HAL (Hybrid Assistive Limb) exoskeleton uses EMG signals to support walking, and an ankle-foot exoskeleton example controls artificial muscle

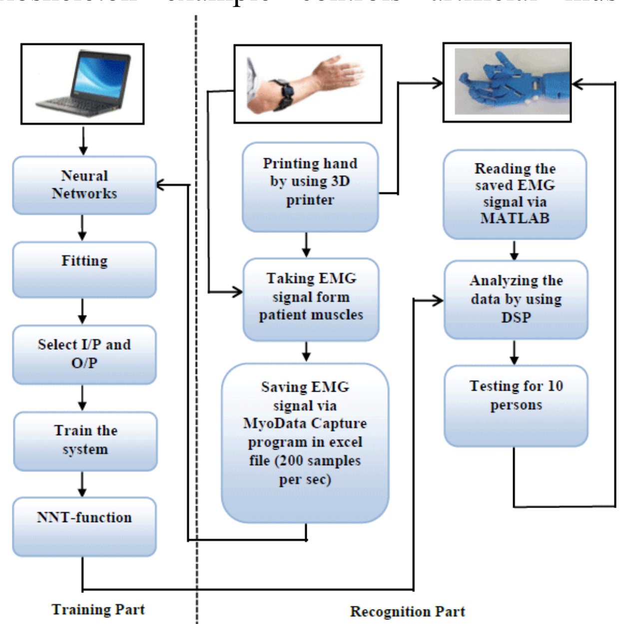

Fig. 11. EMG-based control system pipeline

tension using EMG from natural muscles. The BETTER project combines EEG and EMG for controlling lower-limb exoskeletons in stroke rehabilitation [50].

Electroencephalography (EEG) based control (Brain-Controlled/Brain-Machine Interface - BMI) utilizes electrical activity in the brain and can be used to control robots, especially for users with severe motor impairments.

BMIs can offer continuous control of position/velocity or discrete control of intended targets or actions. EEG signals are useful because their usability is not limited by the level of physical disability; brain activity related to movement intent can be recorded even if the limb cannot move. However, EEG signals can be variable and affected by mood or attention and may not be suitable for children with brain damage. The CP walker and Exohand-2 are examples of devices using EEG signals [51]. As mentioned before, the BETTER project also utilizes EEG.

D. Adaptive and Learning-Based Control

These systems can adjust their parameters or behavior over time based on user performance, environmental changes, or pre-learned patterns. Adaptive controllers can adjust their parameters in response to changes in the system or uncertainties. Adaptive control with active disturbance rejection (ADRC) is one such method [52]. In gait rehabilitation, adaptive control algorithms can reduce torque, allowing the patient to apply their own force, or adjust assistance based on EMG signals. In shared autonomy control is shared between the human user and the robot's autonomous capabilities. This can reduce the cognitive and physical load on the user by allowing the machine to handle certain aspects of a task. A key challenge is determining how to appropriately share control and adapt to this sharing as the user's abilities change.

E. Interface-Driven Control

This refers to control systems primarily defined by the type of human-machine interface (HMI) used to command the robot. For example, joysticks, sip-and-puff, switches are common interfaces, especially for wheelchairs and some robotic arms. Joysticks offer proportional control, while sip-and-puff and switch arrays often provide non-proportional control. The Robotic Exoskeleton (REX) uses joystick interaction [52]. Moreover, haptic interfaces allow users to feel forces and textures, providing a more intuitive control experience and valuable sensory feedback. Haptic feedback can guide user trajectories or alert them to obstacles. Nowadays, voice commands can be used for natural language instructions to robots, especially for tasks like fetching items. These systems are considered cheap and accessible. Finally, body-powered control uses different body parts to trigger the rehabilitation robot. For example, the Ekso robot can be activated by the user shifting their body weight [53].

F. Multimodal Control

These describe the overall structure of how control signals are processed and fed back into the system. In open loop control the robot executes pre-programmed movements without considering real-time feedback from the user or environment. This might be used in initial rehabilitation stages where precise control is less critical. On the other hand, the closed-loop control systems use feedback (e.g., from sensors measuring position, force, or physiological signals) to continuously adjust the robot's actions. PID (Proportional-Integral-Derivate) control widely used closed-loop control method known for its simplicity and ability to provide stable and efficient control for various tasks. These systems can be combined and use elements from open- and closed-loop controls. The Wearable Orthosis for Tremor Assessment and Suppression (WOTAS) features different operational modes including monitoring (passive measurement), passive (simulating viscosity/inertia), and active (applying opposing forces to tremor), which represents a hybrid approach to control [54].

These categories often overlap, with many therapeutic robots combining multiple control strategies and interface modalities. The goal is to create a system that suits the best to the user’s need and therapeutic goals. For instance, a system might use EMG signals (physiological control) within an impedance control framework (force/impedance control) and adapt its parameters based on user progress (adaptive control). Control systems in therapeutic robotics must often meet stringent requirements for safety and robustness, particularly when used in clinical settings.

V. Case Study: Tremor Assessment and Suppression (WOTAS)

The Wearable Orthosis for Tremor Assessment and Suppression (WOTAS) serves as an in-depth case study illustrating the targeted application of rehabilitation robotics. The goal is to mitigate specific neurological symptoms, in this instance, pathological tremors. Developed by E. Rocon and J. L. Pons, this exoskeleton targets the upper limb, specifically providing three degrees of freedom (3 DoF): elbow flexion-extension, forearm pronation-supination, and wrist flexion-extension, each actuated by dedicated motors (Fig. 13). This mechanical design allows WOTAS to interact precisely with the primary joints affected by tremors in many patients [54].

To effectively assess and counteract tremors, WOTAS incorporates a following sensing and control system.

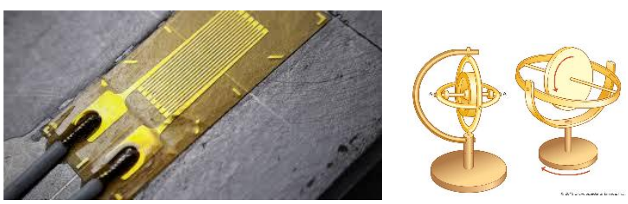

Fig. 12. Strain gauge and gyroscopes

For kinematic data, the system utilizes gyroscopes to measure the speed and nature of the arm's movement, specifically the tremor. These gyroscopes are crucial for detecting rhythmic, involuntary oscillations characteristic of tremors. The raw sensor data undergoes filtering, typically within a bandpass of 0.3Hz to 25Hz, to isolate tremor frequencies from voluntary movements. For kinetics, strain gauges are employed to measure the forces or torques, providing insights into the interaction between the orthosis and the user's limb.

The WOTAS system is comprised of three main components. The Orthosis is the wearable brace itself, encompassing the mechanical structure, the integrated sensors (gyroscopes, strain gauges), and the actuators (motors) that apply forces (Fig 12). Control Unit houses an acquisition card, acting as the critical interface. It collects data from the sensors on the orthosis and transmits control signals to the actuators, based on the algorithms implemented by the controller. Remote Computer manages the overall WOTAS system, likely for high-level control, data logging, and user interface functions.

WOTAS can operate in distinct modes to address tremors:

Monitoring Mode: In this passive state, WOTAS simply measures and records the tremor characteristics without actively intervening 9 8. This mode is essential for establishing a baseline understanding of the patient's tremor.

P*assive Suppression Mode:* Here, the orthosis simulates an increase in the limb's viscosity (resistance to speed) and inertia (resistance to changes in motion). By making the limb feel "heavier" or "slower to move," it can passively damp down the tremor oscillations.

Active Suppression Mode: This is the most direct intervention. The system estimates the involuntary

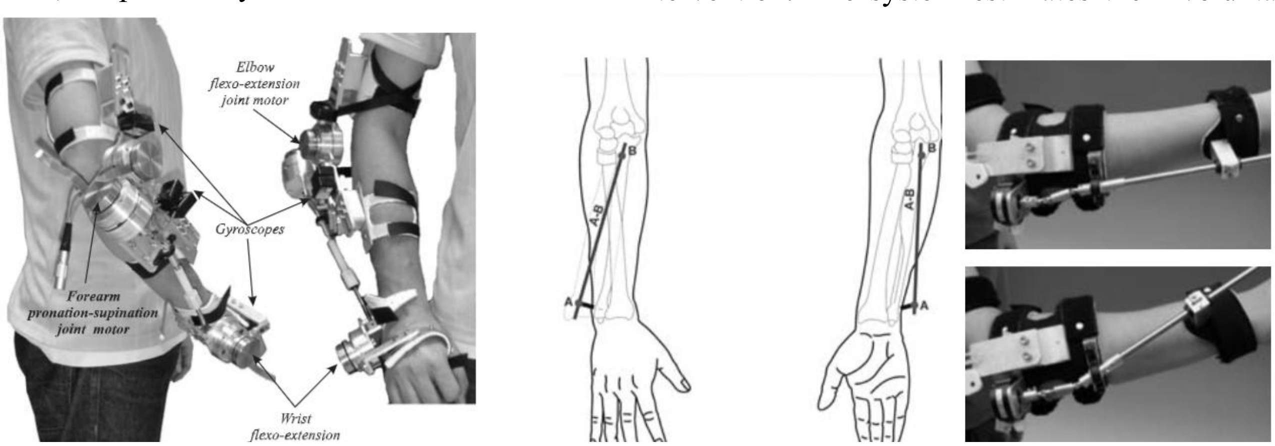

Fig. 13. DoF elbow flexion-extension, forearm pronation-supination, and wrist flexion-extension.

tremor movement in real-time and then commands its actuators to apply forces directly opposing that tremor. This "direct counterattack" aims to cancel out the tremor motion actively.

The effectiveness of WOTAS was evaluated through a structured experimental protocol involving 10 patients with various tremor-related diseases 10. A key aspect of the study design was blinding while the operator knew the active WOTAS mode, the patient, therapist, and doctor were unaware, helping to mitigate the placebo effect 10. Participants performed standard clinical tasks used by neurologists for tremor diagnosis, such as keeping arms outstretched, touching the nose, maintaining a resting limb position, and drawing a spiral.

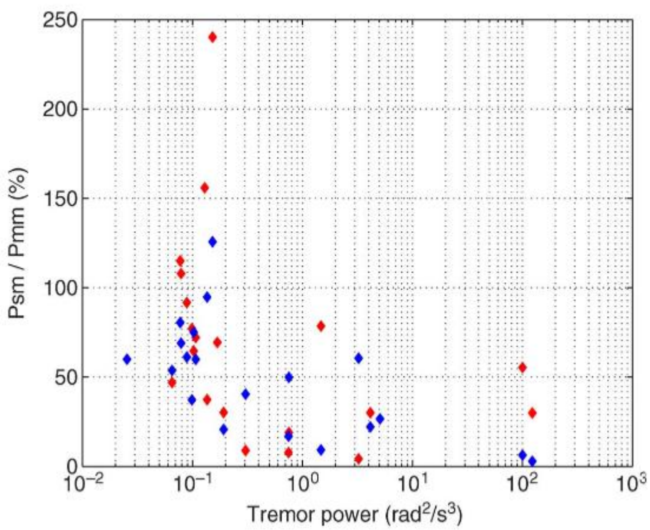

Fig. 14. Tremor reduction (y axis) achieved by WOTAS operating in suppressing both in active (blue markers) and passive (red markers), mode. x axis represents users' tremor energy with WOTAS in monitoring mode.

Tremor reduction was quantified using a "Figure of Merit" (R), calculated as the ratio of tremor power when WOTAS was in a suppression mode (Psm) to the tremor power when WOTAS was just monitoring (Pmm) , expressed as a percentage ($R = (Psm / Pmm) * 100$). A lower R value indicated better suppression. The results demonstrated considerable efficacy.

The active suppression strategy achieved an average tremor power reduction of 81.2%. The passive suppression strategy resulted in an average tremor power reduction of 70%.

The study concluded that it successfully demonstrated the feasibility of suppressing tremor using a wearable robotic exoskeleton that applies biomechanical loads to the limb. This detailed examination of WOTAS highlights how targeted robotic design, sophisticated sensing, intelligent control, and rigorous experimental validation can lead to effective solutions for complex neurological symptoms, significantly improving the potential for functional improvement.

VI. Manipulation Aids Robotics

Robotic manipulation aids are specialized devices designed to help individuals with limited upper limb functions perform everyday tasks independently. These systems emerged as a crucial solution for people who have severe upper limb impairments but retain cognitive ability to control assistive devices. The primary goal is to enable users to manipulate objects and perform essential ADLs without constant assistance from caregivers. Safety remains paramount in manipulation aids due to their close interaction with users. Basic safety measures incorporate:

- Limited workspace volume
- Low operational velocities
- Force/torque feedback sensors
- Automatic stop functions when detecting obstacles
- Fail-safe mechanisms

Modern systems have evolved to include advanced safety features such as machine vision systems for real-time environment monitoring, proximity sensors that create safety zones around the user, and smart force control algorithms that can distinguish between intended interactions and unintended collisions. Additionally, current technologies implement compliant actuators that yield under excessive force, sensor systems for fault tolerance, and emergency stop buttons accessible to both user and caregiver. The physical design focuses on safety through soft padding and rounded edges on all contact surfaces, while the control system continuously monitors motor currents and joint torques, adapting speed based on task complexity.

Clinical studies have demonstrated significant benefits for users of robotic manipulation aids. Users consistently show marked improvements in independence during daily tasks like feeding, drinking, and personal hygiene. The ability to perform work-related activities increases substantially, while dependency on caregivers decreases notably. Studies indicate enhanced quality of life and psychological well-being, along with greater participation in social activities.

Research shows that users typically become proficient with these devices after approximately 13 hours of training, demonstrating improved performance in over 50% of common ADL tasks [55]. Notable improvements are particularly evident in object retrieval from various heights, drinking and feeding tasks, basic grooming activities, simple household tasks, and workplace activities.

The future of robotic manipulation aids looks promising with several emerging developments. Artificial intelligence integration is advancing user intent recognition capabilities, while advanced shared control systems are better blending user commands with autonomous functions. Control interfaces are becoming more intuitive, with brain-computer interfaces showing particular promise. Physical designs are trending toward lighter, more portable solutions with improved power efficiency. Enhanced haptic feedback systems provide better user control, while integration with smart home systems is expanding functionality. Cloud connectivity enables remote monitoring and support, and adaptive learning algorithms are personalizing device behavior to individual users.

Control system remains a central focus in development efforts. Manufacturers are exploring more sophisticated control processes to make the users feel more intuitive while using the devices.

IV. Control Systems in Manipulation Aids

The control systems embedded within robotic manipulation aids are fundamental to their success, as they directly mediate the user's ability to perform essential activities of daily living and vocational tasks. Unlike therapeutic robots primarily focused on motor relearning, the control for manipulation aid is focused on prioritizing intuitive task execution, seamless integration into the user's life, and robust safety in often unpredictable everyday environments. The design of the control interface itself is a critical factor, heavily influencing user acceptance and the overall functionality of the assistive system

A. User-Centric Control Modes

A core aspect of manipulation aid control lies in providing users with modes that translate their intentions into effective actions on objects in their environment. While foundational control methods like joint control and Cartesian control are utilized, their implementation is tailored to the practical needs of performing daily tasks. In joint control mode, as exemplified by early versions of the RAPTOR arm (Fig. 15), the user individually commands each of the robot's degrees of freedom—such as shoulder flexion/extension or elbow rotation [56]. While this approach offers directness in one sense and can be simpler to implement from an engineering perspective, it often imposes a significant cognitive load on the user. They must mentally decompose a desired end-effector movement (e.g., picking up a glass) into a sequence of individual joint adjustments, which can be cumbersome and unintuitive for complex tasks.

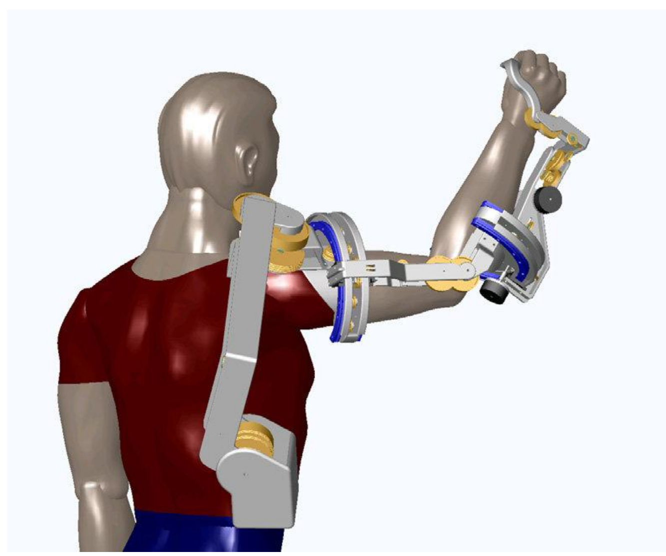

Fig. 15. 7-DoF robotic exoskeleton-style arm that visually resembles the early RAPTOR manipulator's multi-joint setup

In contrast, Cartesian control modes generally offer a more intuitive pathway for task-oriented manipulation. Here, the user directly commands the position and orientation of the robot's end-effector within a three-dimensional Cartesian coordinate system (e.g., moving the gripper forward, left, or rotating it). The underlying control system, leveraging an inverse kinematical model, then automatically calculates the complex sequence of joint angles required to achieve this desired end-effector pose. The ARM (Assistive Robotic Manipulator), formerly known as MANUS, notably provides both task space (Cartesian) control and joint space control, granting users flexibility depending on their preference or the specific nature of the task at hand [27]. This adaptability is crucial for individuals who rely on these aids for a diverse range of ADLs, from eating to operating household devices. To further streamline common activities, some advanced manipulators integrate specialized task modes. For example, the ARM system features a pre-programmed "drinking mode" that can replicate the motion of bringing a cup to the mouth, and a "folding mode" to conveniently stow the arm when not in use. Similarly, the My Spoon, a dedicated 5-DOF manipulator arm for eating assistance, can be operated in manual or semi-automatic modes via a joystick, greatly simplifying the complex coordination required for the feeding task [57].

B. Human-Machine Interfaces

The Human-Machine Interface (HMI) serves as the crucial bridge between the user's intent and the robot's actions, and its design is paramount for the successful adoption and daily use of manipulation aids. Users must interact with these systems frequently and for a wide variety of tasks, making ease of use and intuitiveness essential. Standard adaptive interfaces, such as joysticks, keypads, or sip-and-puff devices, remain common input methods for controlling robotic arms. For instance, the Winsford Feeder (Fig. 16), a task-specific device for eating, can be controlled simply by a chin switch or a plug-in rocker switch, enabling users to manage their eating rate with minimal physical input.

However, the field is continually exploring advanced interface technologies to further reduce user burden and enhance the naturalness of interaction. Voice control offers a hands-free command modality; systems like FRIEND, which integrates an electric wheelchair with the ARM manipulator, can be commanded through a speech interface [58]. Recognized words are displayed on a screen, allowing the user to monitor the system's

Fig. 16. Winsford Feeder manipulation aid robot.

understanding and react quickly if an error occurs, thereby improving both usability and safety.

Users might also employ speech commands to activate specific system functions or to indicate desired objects within the robot's workspace. Wagner JJ, Smaby N, Chang K, C. Burgar. ProVAR assistive robot interface [Internet]. 1999. Available from: https://www.researchgate.net/publication/240198023_ProVAR_assistive_robot_interface [59].

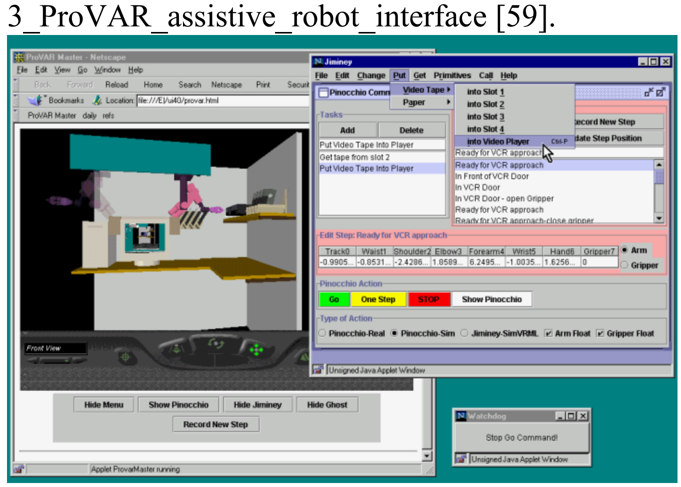

Fig. 17. The 3-D world model of ProVAR interface. The representation of the user's work area contains a "live" robot model showing the position of the real robot and a "virtual" robot model that the user can move to set new goal positions.

This virtual environment allowed users to plan and examine tasks, such as object retrieval or manipulation, before commanding the robot to execute them in the real world, potentially reducing errors and improving task efficiency. Research has also delved into gesture recognition, where users might indicate locations or desired objects by pointing with a laser pointer, offering a more direct and less abstract method of communication. The diagram illustrates an integrated system for robot programming using both virtual and physical human-machine interfaces (HMIs). Despite the promise of these advanced HMIs, they are not without challenges. Issues such as reliability, the complexity of calibration and setup, and the cognitive demands of learning new interaction paradigms can hinder their practical application. Consequently, designing truly intuitive, reliable, and effective interfaces that cater to a diverse user population with varying abilities remains a significant ongoing challenge in the development of robotic manipulation aids.

C. End-Effector Interaction

Manipulation aids must possess control systems that enable their end-effectors to grasp, hold, move, and release objects with precision and reliability. Most contemporary manipulation aids employ a relatively simple pincer-like gripper as their end-effector. While this design inherently limits the range and complexity of manipulations that can be performed (e.g., complex in-hand manipulation is typically not possible), a large portion of essential ADL and vocational tasks, such as picking up a phone, opening a drawer, or holding a utensil, involve straightforward pick-and-place actions that such grippers can adequately execute.

To enhance the robustness of grasping and manipulation, especially in unstructured environments where object properties may not be perfectly known, end-effectors are increasingly being equipped with sensors. This allows for sensor-enhanced grasping, where feedback from these sensors informs the control system's actions. The PROVAR system, for instance, integrated force-sensitive resistors and optical emitter/detector pairs into its end-effector [59]. This sensory information helps the robot detect the presence of an object within its grasp, confirm successful contact, and potentially modulate grip force to prevent crushing fragile items or losing hold of heavier ones, leading to more reliable and safer manipulation. Furthermore, innovative control strategies are being developed to improve the process of approaching and interacting with objects. The ARM system's "collaborative control mode" is an interesting example: a small camera mounted on the robot's end-effector provides a close-up view of the target object, and the image from this camera is used directly in the control loop to guide the arm's approach. This approach could significantly reduce the time and effort required for the user to finely position the arm for grasping, although it might introduce a slightly longer duration for the initial selection of the object within the camera's limited field of view.

D. Multifunctional Assistive Ecosystem

Many individuals with severe disabilities rely on multiple assistive devices, such as a powered wheelchair for mobility and a robotic arm for manipulation. Managing separate control interfaces for each device can be cumbersome and cognitively demanding. Integrated control systems aim to address this by allowing a single control interface—be it a joystick, a head switch array, a voice recognition system, or a keypad—to operate two or more assistive devices. This integration, forming an integral aid, can offer significant convenience and empower users to function as independently as possible. An evaluation study of an early version of the MANUS system, for example, reported that users had trouble when trying to control their wheelchair and the robotic arm simultaneously using two separate joysticks. Consequently, the current MANUS system allows the same joystick to be used for controlling both the wheelchair and the arm, streamlining operation (Fig 19). Similarly, research has demonstrated integrated control schemes where the same joystick was used to command an electric wheelchair and a desktop-mounted robotic arm when the wheelchair was positioned in proximity to the workstation, facilitating vocational tasks.

The control architecture for these systems (Fig. 18) presents unique challenges, particularly when dealing with redundant robots such as wheelchairs equipped with robotic arms that possess nine or more degrees of freedom. This redundancy creates infinite solutions for inverse kinematic problems, requiring sophisticated algorithms to determine optimal joint configurations for specific tasks. The typical scenarios these robots must handle include complex

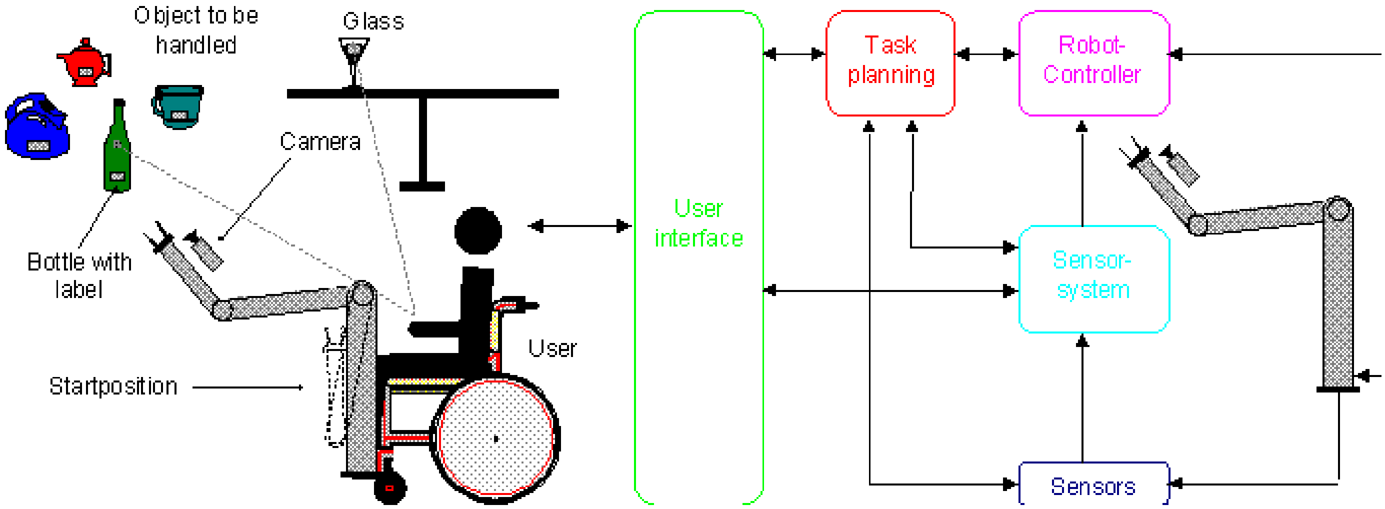

Fig. 18. Scenario and principal control structure for a wheelchair with coupled robot arm.

activities of daily living such as drinking assistance, meal preparation, and eating support, each requiring precise coordination between the mobile base and manipulator arm. The automation system must address critical areas including high-level task specification and automatic division into subtask sequences, object identification and localization with operational instructions, gripper movement considering obstacles and environmental constraints, and object grasping strategies adapted to various shapes and gripper configurations.

Sensor-based control emerges as a crucial component, with visual information playing the primary role due to its ability to handle complex environmental data. However, scene interpretation remains a significant scientific challenge, necessitating user cognitive support to identify objects within captured images. The integration of distributed information systems, such as barcode markers or chip card processors embedded in objects, offers promising solutions for simplifying software complexity while providing handling strategies and object characteristics. This approach leverages the cognitive abilities of users, particularly those with physical impairments but intact mental faculties, to support and enhance the automation system's performance.

Vision-based motion control utilizing stereo camera systems provides the most viable solution for depth perception and three-dimensional object manipulation. The calibration challenges associated with mobile platforms require robust visual control methods that operate directly in image space rather than relying on precise geometric calibration. Advanced techniques enable the entire handling process, from object approach through obstacle avoidance to final grasping, to be performed using image plane coordinates exclusively. This calibration-independent approach significantly reduces maintenance requirements and enhances system reliability, addressing the practical constraints of home-based rehabilitation environments.

Fig. 19. Wheelchair with MANUS robot arm as an real example for a mobile basis with robot arm.

The control of robots with more than six degrees of freedom introduces computational complexity that must be managed within the power and processing limitations of wheelchair-based systems. Novel analytical solutions using imaginary links to reduce redundant systems to six degrees of freedom provide computational efficiency while maintaining solution accuracy and insight into structural influences. This approach is particularly valuable for service robot applications where computational power is limited by cost constraints and available electrical power from wheelchair batteries.

Programming by demonstration represents an innovative approach to reduce the technical expertise required for system adaptation and customization. This method allows users or caregivers to teach robots new tasks through natural demonstration rather than complex programming languages. However, significant challenges remain in analyzing human intentions during demonstrations and accounting for the closed-loop nature of human-object interactions. The automatic generation of appropriate control loops and regulatory mechanisms from demonstration data continues to be an active area of research, particularly for tasks involving sensory feedback such as liquid pouring or force-sensitive manipulation.

However, the convenience of integrated control is not without potential drawbacks. One significant concern is the "all-or-nothing" problem: if the single input device malfunctions or breaks, the user may lose access to every operation mode for all connected devices, potentially leaving them stranded or unable to perform critical tasks [60]. Furthermore, the cognitive load associated with switching between different control modes within a single integrated controller can sometimes be more demanding for the user than simply using separate, dedicated input devices for each assistive technology. Careful design and user training are therefore essential to mitigate these challenges and ensure that integrated control truly enhances rather than complicates the user's experience.

E. Safety-Focused Control in Dynamic and Unstructured Environments

Safety is an important concern in the design and control of robotic manipulation aids. Since these devices operate in close physical proximity to the user in home and dynamic environment, it's less predictable behavior rather than controlled clinical settings. To inherently enhance safety, existing manipulation aids are typically designed with limitations on their physical capabilities, such as restricted workspace volume (how far they can reach), low operating velocity, and low force output (Table 2). While these design choices reduce the risk of injury from accidental collisions or uncontrolled movements, they can also lead to limitations in functionality. For example, a survey among MANUS users revealed that many found robots to move too slowly; to be unable to handle objects they considered to be of reasonable weight, or to lack the physical reach necessary to accomplish certain desired movement tasks [27]. Designing manipulators that are faster, stronger, and have greater reach without compromising safety is not an easy problem.

To proactively manage safety, sensor-based safety systems are often incorporated. Machine vision and proximity sensors, for instance, have been utilized to help the robot distinguish between human users and inanimate objects in its environment, enabling the control system to automatically halt or slow down the robot's movement if it detects that it is moving too closely towards the user or another obstacle. Beyond collision avoidance, fail-safe mechanisms are also critical. Fail-safe force sensors can be integrated into the robot's structure or end-effector to realize safe force/torque feedback. This allows the end-effector to make controlled physical contact with the user, when necessary, for instance, during personal care tasks like feeding or grooming—while ensuring that the applied forces remain within safe and comfortable limits. Furthermore, research continues into collision-mitigating designs that aim to reduce the potential harm from uncontrolled collisions without unduly sacrificing the robot's performance. An example is the prototype manipulator developed by Zinn et al., which sought to reduce the impact loads associated with collisions by, among other strategies, relocating the major source of actuation effort from the joints to the base of the robot to reduce link inertia, and using small, low-inertia servomotors collocated at the joints to maintain torque capability. These multi-faceted approaches to safety are essential for building user trust and ensuring the practical viability of robotic manipulation aids in real-world applications.

Ultimately, the control systems for robotic manipulation aids are meticulously engineered to achieve a delicate balance between task efficacy, user convenience, and operational safety within the complex and varied contexts of daily life . While they draw upon foundational control principles also seen in therapeutic robotics, their specific design, implementation, and prioritization of features are distinctly shaped by the overarching goal of restoring functional independence and enhancing the quality of life for individuals with upper limb impairments.

TABLE 2

[2] Safety and Functionality Trade Off in Robotics Manipulation Aids

Safety Feature	Purpose	Functional Trade-off	Example Scenario
Low Operational Velocity	To prevent high-impact collisions with the user or environment	Task takes longer to perform	Pouring a glass of water or retrieving a ringing phone becomes a slow
Limited Force & Payload Capacity	To prevent the arm from crushing objects	The arm is unable to lift or manipulate common, moderately heavy household items, limiting its utility for many daily tasks.	The arm can successfully retrieve a fork but cannot lift a full carton of milk from the refrigerator or a heavy textbook from a bag.
Collision Avoidance & Proximity Sensors	To automatically halt the arm before it makes physical contact with an obstacle	The arm may refuse to enter cluttered or tight spaces, creating "no-go zones"	The arm stops short when trying to retrieve a dropped item from the narrow space, even though the object is visible.
Restricted Workspace / Limited Reach	To ensure the arm cannot move into areas where it might endanger the user's head or face	The user is unable to reach objects outside the pre-defined "safe" bubble.	The user cannot reach the top kitchen cabinet to get a box of cereal or press a button on a high elevator panel.
Simple Gripper Design (e.g., Pincer)	To reduce mechanical complexity, cost, and the number of potential failure points	Pick up objects that have irregular shapes	The arm can easily grasp a cylindrical bottle but cannot pick up a credit card
Fail-Safe Brakes & Emergency Stops	To immediately halt all motion in case of a power failure, system error, or user-triggered command	Trigger an unnecessary shutdown from a minor sensor error or an accidental bump	A sudden, minor power dip causes the arm to lock in place while holding a cup over a laptop, requiring a caregiver to intervene and reset the system.

V. Intelligent Mobility Aids

Intelligent Mobility Aids, or IMAs, are "smart" wheelchairs and walkers designed for people who have trouble safely using standard versions. The main challenge is caused by several disabilities, such as vision problems, tremors, or cognitive difficulties. Analogy can be done as regular mobility devices that have been upgraded to act as its eyes and ears. The main job of an IMA is to help the user get around safely. This help can be quite simple, such as a basic collision avoidance system that acts like a safety bumper to keep the user from running into walls, furniture, or other people. In this case, the user still does most of the steering.

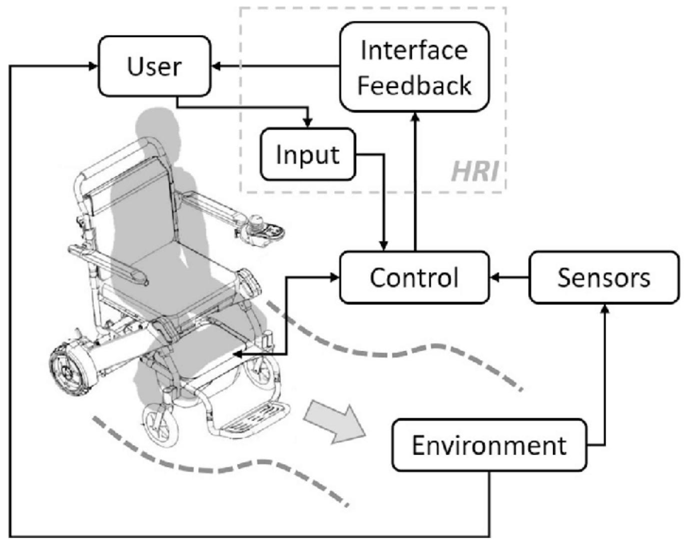

Fig. 20. Intelligent Mobility Aids basic components

On the other hand, some IMAs are much more advanced and can operate like a self-driving vehicle. A user might tell it "go to the kitchen," and the device will use an internal map to navigate there on its own, avoiding obstacles along the way.

To handle complex situations, IMAs use sensors to understand the environment and make decisions based on the input (Fig 20). As mentioned above, the user can also participate in the control, where he receives feedback about the environment and makes the decision. There are also other special driving modes. For example, a "doorway mode" can help guide the user perfectly through a narrow opening, while a "wall-following mode" makes it easy to travel down a long hallway. While this technology is most often seen in smart wheelchairs, it is also used in smart walkers to provide navigational support for people who can still walk but need extra guidance.

Despite their great potential, these devices are not yet widely used. The main barriers are their very high cost, the need for better and more affordable sensors that work reliably everywhere, and the lack of large-scale studies needed to prove their effectiveness to insurance companies for reimbursement.

V. Control Systems in Intelligent Mobility Aids

Intelligent Mobility Aids (IMAs) control systems are engineered to interpret user commands for movement while simultaneously processing complex environmental information to ensure safety and efficiency in navigation.

The primary function of IMA control systems is environmental sensing and reactive navigation. These systems heavily rely on a suite of sensors—such as sonar, infrared, laser rangefinders, and vision systems—to perceive the surroundings. The control algorithms process this sensor data to detect obstacles, identify traversable paths, and recognize potential hazards like drop-offs (e.g., stairs or curbs). For instance, Fig. 21 and 22 show smart wheelchair system is comprised of a Jazzy 600ES electric-powered wheelchair (EPW) with added hardware and software for autonomous navigation and user interface [61]. Mechanical modifications to the EPW

Fig. 21. Retrofitted power wheelchair showing all the added features.

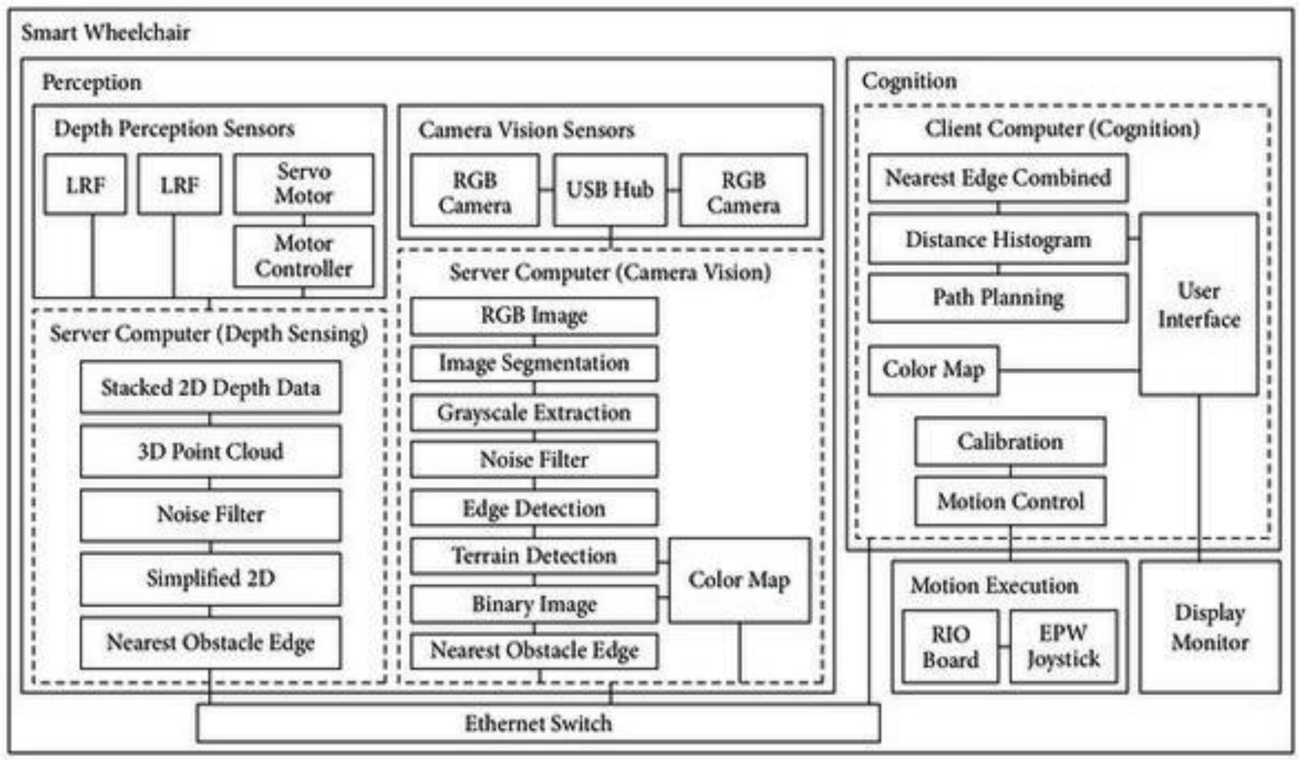

Fig. 22. Computer cluster system architecture.

incorporate a retrofitted footplate with rotating sensor tower at the front of the platform for mounting oscillating LRF sensors for range sensing and color cameras for terrain detection. The autonomous navigation capabilities of the smart wheelchair including perception, localization, path planning, and motion control, operate in the LabVIEW software environment. the NavChair system from the University of Michigan utilizes an array of ultrasonic sensors and employs probabilistic reasoning techniques to combine sensor information with a topological map of the environment [62]. This allows its control system to make adaptive decisions such as automatically steering the wheelchair to avoid collisions or to follow a wall, based on the user's general directional input and the sensed environment.

Similarly, the VAHM (Veteran's Administration/University of Michigan Heuristic Mapper) project incorporated multi-layered control architecture [63]. The VAHM system employs hierarchical, multi-layered control architecture. (Table 3). It is designed to manage complex robotic and assistive environments by distributing computational responsibilities across different abstraction levels. At the lowest layer, direct interaction with hardware is handled through real-time control of actuators and continuous data acquisition from sensors. This layer ensures immediate responsiveness and stability in low-level operations. The intermediate (cluster) layer groups related sensors and actuators into functional units, each managed by local controllers running Monitor–Analyze–Plan–Execute (MAPE) feedback loops. These local clusters are capable of semi-autonomous behavior, adjusting to dynamic conditions within their domain. Above this, the supervisory layer coordinates multiple clusters, managing interdependencies and optimizing regional behaviors through heuristic reasoning and contextual decision-making. Finally, the strategic (top-level) layer is responsible for global system goals, dynamic task allocation, and adaptive reconfiguration based on

TABLE 3
[3] VAHM SYSTEM LAYERS ARCHITECTURE

Layer	Description
Layer 0 (Sensors/Actuators)	Direct control of subsystems; continuous measurement and feedback
Layer 1 (Cluster-level Control)	Local controllers executing MAPE loops on sensor clusters
Layer 2 (Regional/Supervisory Control)	Aggregation, coordination across multiple lower clusters
Layer 3 (Top-level Optimization/Strategic)	Overall system planning, dynamic reconfiguration, resource optimization

high-level objectives and user intent. Communication across layers is structured to allow upward reporting of state and constraints, and downward delegation of goals and permissions, enabling the system to operate adaptively and efficiently in uncertain, real-world environments.

Its lowest reactive layer used a subsumption control approach for immediate sense-react behaviors (like stopping before an obstacle), while higher layers handled more deliberative reasoning and control based on a learned map of the environment.

User interface and shared control are critical aspects. Users interact with IMAs through various input devices, including joysticks (offering proportional or discrete control), head switches, sip-and-puff systems, or even voice commands. The control system must effectively translate these often-limited user inputs into smooth and intended wheelchair movements. Many IMAs implement shared control paradigms, where the system assists the user rather than taking over completely. For example, the user might provide a general direction, and the IMA's control system refines the trajectory to smoothly navigate through a doorway or around an obstacle. The TinMan smart wheelchair allowed users to manually adjust the level of assistance provided by the obstacle avoidance system, catering to individual preferences and capabilities (Fig 23) [64]. The TAO (Transportable Adaptable Operator) system used a subsumptive reasoning system, where different behavioral modules (e.g., "follow wall," "avoid obstacle," "go to goal") competed or cooperated, allowing the most appropriate behavior to emerge based on the current context and user input. The TAO system is a behavior-based control architecture developed to support adaptive, semi-autonomous navigation in assistive robotic platforms such as smart wheelchairs. Its design follows the subsumption architecture, where multiple behavior modules—such as avoid obstacle, follow wall, and go to goal—operate in parallel and are hierarchically organized (Fig. 24).

Fig. 23. TinMan smart wheelchair

Each module independently processes sensor data

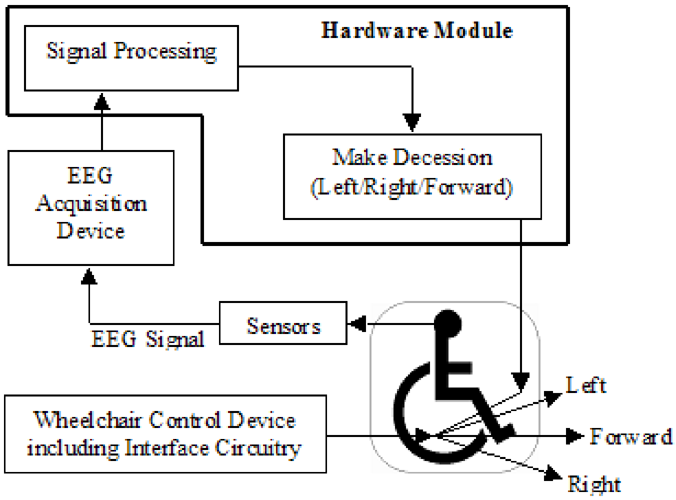

Fig. 24. TAO wheelchair system architecture

and generates control commands based on its behavioral objective. Higher-priority behaviors can suppress or inhibit lower-priority ones, allowing emergent decision-making that adapts to the environment in real-time without requiring a centralized planner. In the context of the TAO wheelchair, this architecture enables flexible and robust operation in dynamic environments. For example, while the user may command forward movement, the avoid obstacle behavior can override that input temporarily to steer around an obstruction.

Path planning and execution are more advanced features found in some IMA control systems. Systems like Wheelesley were designed to build maps of their environment and then plan and execute paths to user-specified destinations, navigating autonomously while still allowing for user intervention. The OMNI (Office-/Mobility Navigation Interface) wheelchair was developed to

Fig. 25. TAO smart wheelchair

operate in office environments, capable of learning and following predefined paths, such as circular or elliptical trajectories around objects, based on initial user guidance [65]. The OMNI (Office-/Mobility Navigation Interface) wheelchair was developed for indoor use. It is especially useful in office environments (Fig 26). The system helps people with mobility impairments move more easily. It supports both manual and autonomous control. The main idea of OMNI is learning and replaying paths. The user first drives the wheelchair along a path. This path can go around desks, chairs, or other furniture. OMNI records this movement in real-time. It captures direction, distance, turning angles, and speed. The system saves this information to memory. Once a path is learned, OMNI can repeat it automatically (Fig. 27). The user does not need to steer again. The wheelchair follows the same route by itself. This reduces the physical effort for the user. It also makes navigation in familiar spaces much easier. OMNI supports different path types. It can follow straight lines, circles, ellipses, and more complex shapes. It is good for environments where the layout does not change often. For example, it can go around a conference table or follow a hallway loop. The system includes various sensors. These helps detect walls, furniture, and other obstacles. If something is in the way, OMNI can stop or adjust its route. Safety is a key feature. The sensors help avoid collisions. The wheelchair also moves at a safe speed during autonomous operation. The user can take control at any time. The system allows switching between manual and automatic modes. This gives the user more freedom and confidence. They can decide when they want help and when they want to drive themselves. OMNI is designed to work with existing powered wheelchairs. The system can be added as an upgrade. It does not require a new wheelchair. This makes it more affordable and easier to adopt. Installation can be done quickly. The interface is user-friendly. It often uses a joystick or touchscreen. Some versions also include voice or gesture input. The system can be customized to the user’s needs. OMNI also helps reduce cognitive load. In a known environment, the user does not need to plan every move. They can simply activate a saved path and let the wheelchair do the rest. This is helpful for users with both physical and cognitive limitations. The system can store multiple paths. Users can name and choose which one to follow. For example, “office loop” or “bedroom to bathroom.” This makes daily routines more consistent. The memory system is

Fig. 26. OMNI omnidirectional platform that was set up for experimentation and validation.

non-volatile. This means paths are saved even when the wheelchair is turned off. The system is also able to handle small changes in the environment. If a chair is moved slightly, OMNI can still find its way. Battery use is efficient. OMNI does not require much Visualization of human-centered person-following task for domestic assistance: the omnidirectional capability allows the rover to follow the user maintaining its orientation towards them while avoiding obstacles. (**a**) The robot can follow the same path of the person while avoiding obstacles. (**b**) The robot must follow a different path keeping active the monitoring of the person.extra power. It works well with the standard battery system of a powered wheelchair. Engineers designed OMNI with modularity in mind. This means new features can be added easily. For example, cameras or mapping systems can be added in future upgrades. OMNI’s approach is based on shared control. The system does not take full control away from the user. Instead, it works alongside them. The goal is to support independence, not replace it. The project focused on real-world use. It was tested in environments like offices, labs, and care centers. Feedback from users helped improve the design. Many users said they felt more confident and less tired when using the system. Researchers behind OMNI also studied path-learning algorithms. They focused on making them fast and reliable. The system needs only one demonstration to learn a path. This makes it practical for daily use. OMNI is different from fully autonomous systems. It

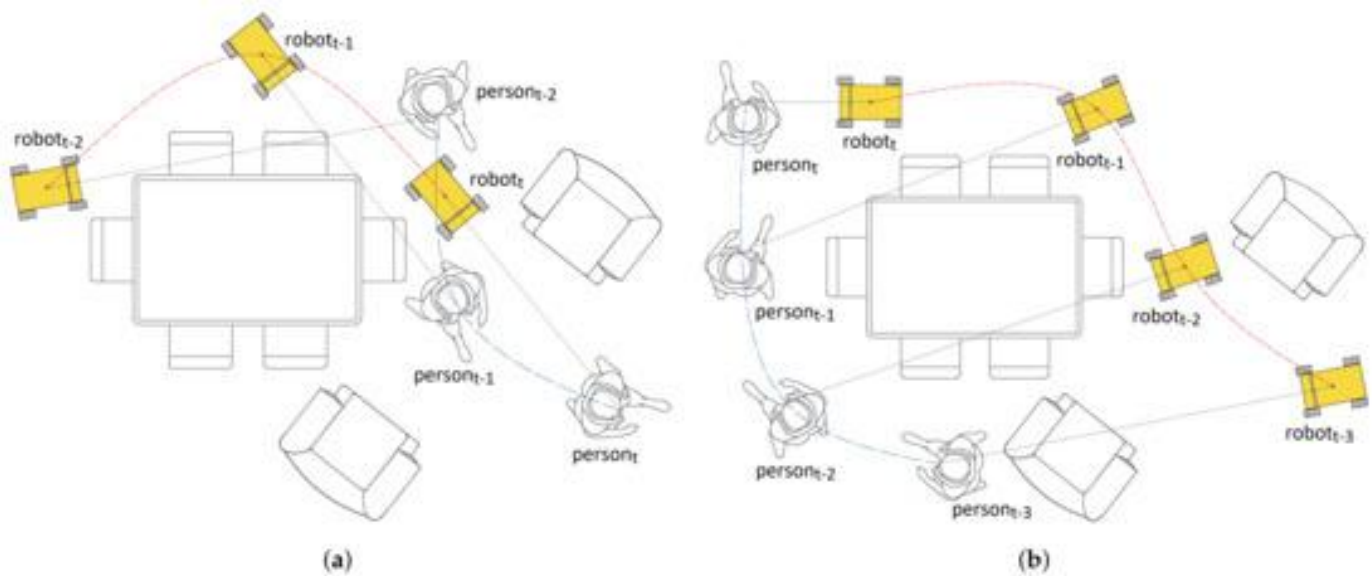

Fig. 27. Visualization of human-centered person-following task for domestic assistance: the omnidirectional capability allows the rover to follow the user maintaining its orientation towards them while avoiding obstacles. (a) The robot can follow the same path of the person while avoiding obstacles. (b) The robot must follow a different path keeping active the monitoring of the person.

does not rely on global maps or full SLAM (simultaneous localization and mapping). Instead, it uses a simpler method. This makes it faster and more robust in fixed environments. The system can also handle minor localization. If the wheelchair starts slightly off the learned path, it can correct itself. This helps it stay accurate even after bumps or small errors. Some versions of OMNI also include learning from repetition. If the user drives the same path many times, OMNI can learn it automatically. This makes setup even easier. The project was an important step toward smarter assistive devices. It showed how machine learning and simple autonomy can improve everyday life. The system does not require a complex AI. Instead, it relies on well-designed behavior and usability.

Adaptive control also plays a role where the system might adjust its level of assistance based on the perceived skill of the user or the complexity of the environment. The goal is to provide enough support to ensure safety and reduce driving effort, without making the user feel a loss of control. Challenges in IMA control include robustly handling dynamic environments (e.g., moving people), ensuring reliability across diverse conditions, and addressing user acceptance, as some users may find early IMAs too slow, bulky, or overly "intelligent". The development of more sophisticated sensor fusion techniques, intelligent decision-making algorithms, and intuitive human-machine interfaces continues to drive progress in making IMAs more effective and user-friendly tools for enhancing personal mobility.

VII. Performance Evaluation and Clinical Validation

The true measure of rehabilitation robotics lies in its ability to deliver benefits to patients, assessed through both technical performance metrics and clinical validation. This evaluation is multifaceted, encompassing the robots' operational capabilities, their impact on patient outcomes, adherence to safety standards, and overall cost-effectiveness. Evaluating the technical performance of rehabilitation robots is essential to ensure they function reliably, accurately, and safely. Key metrics include precision and repeatability of movements, which are fundamental advantages of robotic systems over manual therapy. Robots can achieve very precise torque moments, an aspect that is often subjective in traditional manual therapy. The use of optical encoders for measuring position and angular speed ensures precise motion control [66]. Advanced control systems, such as Adaptive Control with Active Disturbance Rejection (ADRC), are valued for their ability to withstand uncertainties, parameter changes, and perturbations like a patient's hand tremors, simplifying the control system while enhancing disturbance rejection [67]. Furthermore, the design must ensure reliability; for example, the Wearable Orthosis for Tremor Assessment and Suppression (WOTAS) system utilizes gyroscopes for speed measurement and strain gauges for kinetic data, with signals filtered to focus on relevant frequencies for tremor analysis [54]. The overall technical goal is to create systems that are not only accurate but also robust and adaptable to the dynamic nature of human-robot interaction.

Clinical validation relies on standardized and objective outcome measures to quantify the impact of robotic interventions on patients. Commonly used scales include the Fugl-Meyer Assessment (FMA) for motor recovery, the Wolf Motor Function Test (WMFT) for assessing proximal and distal upper-limb motor control and functional task performance, and the Stroke Impact Scale (SIS) for evaluating function and quality of life across multiple domains from the patient's perspective [68, 89, 70]. Studies often assess improvements in ambulation, motor activity, balance, and overall locomotion skills. For instance, the REX exoskeleton's effectiveness was evaluated using the Berg Balance Scale (BBS) and the Timed Up and Go (TUG) test, demonstrating significant improvements in static and dynamic balance and lower limb motor function compared to standard physical therapy [71. 72]. The Motor Status Score (MSS) is another tool used to evaluate impairment levels [73]. It allows for fine grading of voluntary movement. However, a challenge in comparing clinical trials is the variety of outcome scales used to measure motor movement, strength, walking speed, or functional activities, and the suitability of certain scales can depend on the modality of the robotic therapy administered. There is a recognized need for standardized measurement of sensorimotor recovery in stroke trials to address this variability.

VIII. Limitations

Despite the advancements and demonstrated potential, the field of rehabilitation robotics faces several challenges and limitations that hinder its widespread adoption and optimal utilization.

Human movement is characterized by complex, non-linear kinematics and dynamics, with multiple degrees of freedom (DOF) and time-varying parameters (e.g., joint stiffness, damping). Current control systems often struggle to accurately model and replicate the subtleties of human joint mechanics, such as the shifting instantaneous center of rotation (ICR) in joints like the knee or shoulder. This can lead to kinematic incompatibility, where the robot's movements feel unnatural or impose undesirable constraints on the user.

Many existing control systems, while perhaps adaptive in a general sense (e.g., adjusting overall assistance levels), lack the fine-grained, real-time adaptability needed to respond to the user's rapidly changing physiological state (e.g., fatigue, spasticity, tremor fluctuations, pain) or evolving motor capabilities during a single session or over longer rehabilitation periods. Standardized treatment protocols may not be effective for all patients due to these individual differences.

Physical interaction between a powerful robot and a human, especially one with impaired or unpredictable movements, inherently poses risks. Controllers must guarantee stability and safety even when faced with unexpected forces from the user (e.g., spasms, strong resistance, sudden collapses) or external perturbations. Traditional industrial robot controllers are often not designed for such compliant and safe close-contact interaction.

These control-specific limitations and challenges represent active and vital areas of research. Progress in these domains is essential for developing the next generation of rehabilitation robots that are safer, more effective, more intuitive, and ultimately, more capable of restoring function and improving the quality of life for individuals with disabilities.

VIII. Conclusion

Rehabilitation robotics has evolved from basic mechanisms to sophisticated, AI-driven systems, fundamentally transforming therapeutic interventions. Control strategies have matured from simple positional commands to adaptive, interactive paradigms tailored for therapeutic exercise, daily task assistance in manipulation aids, and safe navigation in intelligent mobility aids, as exemplified by specialized systems like WOTAS. While technical performance, clinical efficacy, safety, and cost-effectiveness are key evaluation benchmarks, significant control system challenges remain. These include accurately emulating human biomechanics, achieving real-time personalization, ensuring robust safety in dynamic interactions, managing sensor imperfections, controlling high-DOF systems, and reliably decoding user intent. Future advancements will leverage AI, advanced sensing, and personalized algorithms to overcome these hurdles, expanding robotic applications in healthcare. Despite persistent challenges, particularly in cost and clinical integration, the field's dedication to enhancing human function and independence ensures that rehabilitation will continue to be a pivotal force in improving the quality of life for individuals with disabilities.

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