International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048
Volume 10, Issue 4, pp 355-362, April-2026
https://doi.org/10.47001/IRJIET/2026.104050

Artificial Intelligence in Control of an Actuated Glove for Hand Rehabilitation

Zlata Jelačić

University of Sarajevo, Faculty of Mechanical Engineering, Department of Mechanics, Sarajevo, Bosnia and Herzegovina

***Abstract* - Hand rehabilitation following neurological injuries requires intensive, repetitive, and task-specific training to restore fine motor function. Actuated gloves – wearable robotic devices that assist finger and hand movements – offer a compact and patient-friendly alternative to traditional robotic arms. This paper presents an AI-driven control framework for an actuated rehabilitation glove, focusing on adaptive assistance, intention recognition, and safe human–robot interaction. The system integrates multimodal sensing, including electromyography (EMG), flex sensors, and force feedback, with machine learning and reinforcement learning algorithms for personalized therapy. A dynamic model of the glove–hand system is introduced, and control strategies combining impedance control and AI-based adaptation are analyzed. The results indicate that AI-enhanced glove systems significantly improve motor recovery, user engagement, and control precision.**

Keywords: rehabilitation robotics, actuated glove, artificial intelligence, hand exoskeleton, EMG control, adaptive assistance.

I. INTRODUCTION

Fine motor recovery of the hand is one of the most challenging aspects of neurorehabilitation. Unlike gross arm movements, hand function requires precise coordination of multiple joints and muscles. Wearable robotic gloves have emerged as an effective solution for delivering high-intensity, repetitive therapy in both clinical and home environments.

Conventional glove systems typically rely on predefined motion trajectories and fixed assistance levels. However, patient capabilities vary dynamically during therapy sessions due to fatigue, recovery progression, and neurological variability. Artificial intelligence (AI) enables adaptive control, allowing the glove to respond to user intent and physiological signals in real time.

This work investigates AI-based control strategies for actuated gloves, emphasizing personalization, safety, and functional recovery [1-2].

II. SYSTEM ARCHITECTURE OF THE ACTUATED GLOVE

The actuated rehabilitation glove is a wearable mechatronic system designed to assist and restore hand function through coordinated actuation and multimodal sensing. The system architecture consists of three main components: mechanical design, sensor integration, and embedded control [3-5].

2.1 Mechanical Design

The glove follows an exoskeletal or soft-robotic structure aligned with human hand anatomy, enabling safe and natural interaction. Due to the high complexity of hand kinematics, the system typically employs **reduced or underactuated configurations** (5–10 DOF) to reproduce essential grasp patterns while maintaining mechanical simplicity (Figure 1).

Figure 1: Mechanical design of the actuated glove

Three primary actuation technologies are used:

- **Cable-driven (tendon-based):** lightweight distal structure, high force transmission, but subject to friction and backlash

- **Pneumatic actuators:** inherently compliant and safe, but nonlinear and less portable
- **Soft actuators:** flexible and comfortable, with limited force output

In many designs, hybrid solutions combine precision and compliance.

The structural design prioritizes:

- ergonomic fit and joint alignment
- low weight and minimal distal inertia
- safe force transmission via compliant elements

2.2 Sensor Integration

The glove incorporates multimodal sensing to capture both system state and user intent (Figure 2):

- **Kinematic sensing:**
  - flex sensors for joint angles
  - IMUs for hand orientation
- **Force sensing:**
  - fingertip or tendon force sensors for interaction measurement
- **Bio-signal acquisition:**
  - surface EMG for muscle activation and intention detection

Figure 2: Sensor integration

Sensor fusion techniques (e.g., Kalman filtering or AI-based models) combine these inputs to estimate joint states, applied forces, and user intent in real time.

2.3 Embedded System and Control Interface

The system is controlled by an embedded architecture consisting of:

- real-time microcontrollers
- communication interfaces (e.g., SPI, I2C, CAN)
- onboard or edge AI processing units

Key requirements include low-latency operation (<10 ms), energy efficiency, and support for adaptive control algorithms.

2.4 Human–Robot Interaction Considerations

The glove operates in direct physical contact with the user, requiring:

- compliant behavior for safety
- transparency during voluntary motion
- adaptability to individual anatomy and impairment level

Effective operation depends on balancing robotic assistance with user effort to support motor learning.

2.5 Design Trade-offs

The system design involves several key trade-offs:

- precision vs. compliance
- force output vs. portability
- sensing accuracy vs. system complexity
- AI performance vs. computational cost

Optimizing these factors is essential for achieving clinically viable and user-friendly rehabilitation devices.

III. ARTIFICIAL ITELLIGENCE FOR GLOVE CONTROL

The integration of artificial intelligence (AI) into the control architecture of actuated rehabilitation gloves represents a fundamental shift from predefined, model-based assistance toward adaptive, data-driven interaction. In contrast to conventional controllers that rely on fixed parameters and simplified biomechanical assumptions, AI-enabled systems continuously learn from multimodal sensory input and dynamically adjust assistance according to the patient's motor capability, intent, and rehabilitation progress. This section elaborates on the principal AI methodologies employed in such systems, including intention recognition, adaptive control through machine learning, and reinforcement learning for personalized therapy optimization [6-8].

3.1 Intention Detection Using EMG and Deep Learning

A central challenge in rehabilitation robotics is the accurate inference of user intent, particularly in patients with impaired or inconsistent motor signals. Surface electromyography (sEMG) provides a direct, non-invasive interface to neuromuscular activity and is therefore widely used as a primary input modality for intention detection in actuated gloves (Figure 3).

Raw EMG signals are inherently noisy, nonlinear, and subject to variability due to electrode placement, muscle fatigue, and inter-subject differences. To address these challenges, modern systems employ deep learning architectures capable of extracting robust and discriminative features directly from the signal. Convolutional neural networks (CNNs) are commonly used to capture spatial and temporal patterns in EMG data, while recurrent neural networks (RNNs), particularly long short-term memory (LSTM) networks, are effective in modeling temporal dependencies and sequential activation patterns.

These models enable the classification of discrete hand actions, such as grasping, pinching, or finger extension, as well as regression-based estimation of continuous joint trajectories or desired force profiles. Importantly, deep learning approaches reduce the need for manual feature engineering and can generalize across different users when trained on sufficiently diverse datasets.

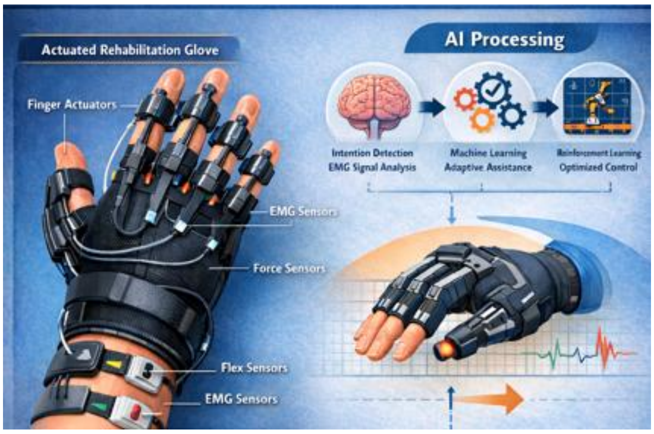

Figure 3: AI processing of the intention detection

In real-time operation, EMG-based intention detection allows the glove to transition from passive assistance to active, intention-driven support, thereby promoting user engagement and motor relearning.

3.2 Adaptive Assistance via Machine Learning

Beyond intention recognition, machine learning plays a critical role in adapting the level and timing of assistance provided by the glove. Rehabilitation is inherently a non-stationary process, as patient capabilities evolve over time due to recovery, fatigue, and therapy progression. Static control strategies are therefore inadequate for maintaining optimal challenge and engagement.

Supervised learning models are often employed to map sensor inputs – suchas EMG signals, joint angles, and interaction forces – todesired actuator outputs. These models can be trained offline using labeled datasets and subsequently fine-tuned online to account for individual user characteristics. Regression techniques, including neural networks and Gaussian process models, are particularly effective for capturing nonlinear relationships between input signals and required assistance.

Unsupervised and semi-supervised learning approaches can further enhance adaptability by identifying patterns in user behavior without explicit labeling. For instance, clustering algorithms may be used to detect different phases of movement or levels of impairment, enabling context-dependent control strategies.

A key concept enabled by machine learning is assist-as-needed control, in which the system provides minimal intervention when the user is capable of performing the task independently and increases assistance only when necessary. This approach has been shown to improve motor learning outcomes by encouraging active participation.

3.3 Reinforcement Learning for Personalized Therapy

Reinforcement learning (RL) offers a powerful framework for optimizing control policies in scenarios where the desired behavior is not explicitly known but can be evaluated through feedback. In the context of rehabilitation gloves, RL enables the system to learn optimal assistance strategies through interaction with the user over time.

In this framework, the glove is modeled as an agent that observes the current state of the system – comprisingsensor data, estimated user intent, and performance metrics – andselects control actions, such as actuator forces or impedance parameters. The agent receives a reward signal based on predefined objectives, which may include minimizing trajectory error, reducing assistance levels, and maximizing user engagement.

Designing an appropriate reward function is critical, as it directly influences the learned behavior. For example, a well-balanced reward function may penalize excessive assistance while encouraging smooth and accurate movements. Over successive interactions, the RL algorithm converges toward a policy that optimally balances these objectives for a given user.

Advanced RL methods, including deep reinforcement learning, allow the system to operate in high-dimensional state spaces and adapt to complex, nonlinear dynamics. However, safety considerations are paramount, particularly in humaninteractive systems. As such, RL is often implemented in a constrained or supervised manner, where learned policies are bounded by predefined safety limits.

3.5 Human-in-the-Loop Learning and Adaptation

A distinguishing feature of AI-driven rehabilitation systems is the incorporation of the human user into the learning loop. Unlike traditional automation systems, where the objective is to minimize human intervention, rehabilitation devices aim to maximize meaningful user participation.

Human-in-the-loop learning frameworks enable the system to adapt not only to physiological signals but also to behavioral and cognitive factors. For instance, user performance metrics, such as task completion time and movement smoothness, can be used to adjust control parameters in real time. Additionally, implicit feedback, such as variations in EMG activation or interaction force, provides continuous information about user effort and engagement.

This bidirectional interaction fosters a cooperative control paradigm, in which both the human and the robotic system contribute to task execution. AI serves as the mediator, continuously balancing assistance and autonomy to optimize therapeutic outcomes.

IV. CONTROL STRATEGIES AND MATHEMATICAL MODELING OF THE ACTUATED REHABILITATION GLOVE

The control of an actuated rehabilitation glove presents a complex problem that involves nonlinear system dynamics, uncertain human interaction forces, and real-time adaptation to user intent. Unlike conventional robotic manipulators, the glove operates in direct physical contact with the human hand, resulting in a tightly coupled human–robot system with shared control authority. Consequently, effective control strategies must simultaneously ensure stability, safety, and adaptability, while accommodating variability in patient behavior and physiological conditions. This section presents a unified framework that combines classical control methods with artificial intelligence, supported by a mathematical model of the glove–hand system [9-10].

4.1 Dynamic Modeling of the Glove–Hand System

The dynamics of the actuated glove interacting with the human hand can be described using a modified rigid-body formulation augmented with compliant interaction terms. The system is modeled in joint space, where the generalized coordinates represent the finger joint angles. The governing equation captures inertial effects, nonlinear dynamics, elastic coupling, and external forces generated by both actuators and the human user.

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + K(q - q_d) = \tau_a + \tau_h$$

In this formulation, the inertia matrix $M(q)$ characterizes the combined mass distribution of the glove and the hand, while the term $C(q,\dot{q})$ accounts for Coriolis and centrifugal effects arising from joint motion. The stiffness matrix K represents the compliant behavior introduced by impedance control, enforcing convergence toward a desired trajectory q_d. The actuator-generated torque or force is denoted by τ_a, whereas $\tau_h\tau_h$ captures the contribution of the human user, which is inherently uncertain and time-varying.

Modeling τ_h accurately is particularly challenging, as it depends on neuromuscular activation, fatigue, and recovery stage. Artificial intelligence methods are therefore employed to estimate or compensate for this term, enabling more precise and adaptive control.

4.2 Impedance-Based Control for Safe Interaction

Impedance control is widely adopted in rehabilitation robotics due to its ability to regulate interaction forces rather than strictly enforcing position trajectories. In the context of an actuated glove, impedance control defines a dynamic relationship between the applied force and the deviation from a desired motion, effectively creating virtual mechanical impedance (Figure 4).

The control objective is to ensure that the glove behaves like a compliant system, allowing the user to influence motion while still providing guidance toward therapeutic trajectories. By adjusting the virtual stiffness and damping parameters, the system can transition between modes of operation, ranging from highly assistive to nearly transparent.

Figure 4: Impedance-based control for saf interaction

Artificial intelligence enhances impedance control by enabling real-time adaptation of these parameters. For example, when the user exhibits strong voluntary effort, the system reduces stiffness to allow greater autonomy. Conversely, when the user struggles to complete a movement, the system increases stiffness to provide additional support. This adaptive behavior is essential for implementing assist-as-needed strategies.

4.3 Assist-as-Needed Control and Human–Robot Cooperation

Assist-as-needed control represents a fundamental paradigm in rehabilitation, aiming to provide minimal intervention while maximizing patient participation. In this framework, the control system continuously evaluates the user’s performance and adjusts assistance accordingly.

The level of assistance is determined based on multiple inputs, including EMG signals, joint kinematics, and interaction forces. Artificial intelligence models process these inputs to estimate the user’s capability and intention, enabling the system to modulate actuator output dynamically.

This approach leads to a cooperative control structure in which both the human and the robotic system contribute to task execution. The human provides voluntary effort, while the glove compensates for deficits, ensuring successful task completion. Over time, as the patient improves, the system reduces its contribution, promoting motor learning and independence.

4.4 Hybrid Control Architecture with AI Integration

To achieve both stability and adaptability, modern rehabilitation gloves employ a hierarchical control architecture that integrates classical control methods with AI-based decision-making. At the lower level, conventional controllers – such as PID or model-based controllers – ensure accurate tracking of actuator commands and maintain system stability. These controllers operate at high frequency and handle the physical dynamics of the actuators.

At the higher level, AI modules process sensory data and generate control objectives, such as desired trajectories, force profiles, or impedance parameters. These modules incorporate machine learning and reinforcement learning algorithms that adapt to user behavior and optimize performance over time.

The interaction between these layers allows the system to maintain robust low-level control while benefiting from the flexibility and learning capability of AI. This hybrid architecture is particularly well-suited for rehabilitation applications, where both safety and adaptability are critical.

4.5 AI-Based Estimation of Human Interaction Forces

A key limitation of traditional control approaches is the inability to directly measure or accurately model the forces generated by the human user. In the glove–hand system, these forces play a crucial role in determining the overall system behavior.

Artificial intelligence provides a means to estimate these interaction forces indirectly using sensor data. By analyzing EMG signals, joint motion, and actuator responses, machine learning models can infer the magnitude and direction of τhτh. This information is then used to adjust control actions, improving both accuracy and responsiveness.

For instance, if the system detects that the user is actively contributing to a movement, it can reduce actuator torque to avoid over-assistance. Conversely, if user effort is insufficient, the system can increase support to maintain the desired trajectory.

V. EXPERIMENTAL VALIDATION

The experimental evaluation was conducted to quantify the effectiveness of the AI-controlled actuated glove in improving hand function during rehabilitation. The assessment focuses on three primary outcome domains: **grasp performance, electromyographic (EMG) activity,** and **range of motion (ROM)**. These metrics collectively capture functional strength, neuromuscular activation, and kinematic recovery [11-12].

5.1 Experimental Setup and Protocol

The study was designed as a longitudinal rehabilitation protocol spanning 8 weeks, during which participants performed structured hand therapy sessions using the actuated glove.

Each session consisted of task-oriented exercises, including (Figure 5):

- cylindrical grasp (power grasp),
- precision pinch tasks,
- controlled finger flexion and extension sequences.

Figure 5: Rehabilitation task-oriented exercises

The glove operated in **assist-as-needed mode**, where AI algorithms dynamically adjusted assistance based on user effort inferred from EMG signals and kinematic feedback.

Data acquisition was performed using:

- **flex sensors** for joint angle measurement,
- **force sensors** for grip force estimation,

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048
Volume 10, Issue 4, pp 355-362, April-2026
https://doi.org/10.47001/IRJIET/2026.104050

- **surface EMG electrodes** for muscle activation monitoring.

Baseline measurements were recorded prior to therapy (Pre-Therapy), and performance was evaluated periodically, with final outcomes reported at the end of the intervention (Post-Therapy).

5.2 Grasp Rehabilitation Performance

Grasp performance was evaluated using three representative functional tasks: **power grasp**, **precision pinch**, and **finger flexion capability**. The results, expressed in metric units, demonstrate substantial improvement across all categories.

For **power grasp**, the average grip strength increased from approximately **7 kg (Pre-Therapy)** to **13 kg (Post-Therapy)**. This nearly twofold increase indicates a significant recovery of global hand and the ability to sustain object manipulation (Figure 6).

In **precision pinch tasks**, which require fine motor control and coordination, the measured force improved from **2.7 kg to 5 kg**. This improvement is particularly relevant for activities involving small object manipulation, such as writing or buttoning, and reflects enhanced neuromuscular coordination.

Figure 6: Grasp rehabilitation performance

For **finger flexion**, the results show improved execution consistency and control, with performance metrics stabilizing around **25% improvement** in movement completion and coordination accuracy. Although expressed differently from force-based metrics, this reflects improved joint control and synchronization across fingers.

These results confirm that the AI-driven control strategy effectively supports both **gross and fine motor recovery**, with measurable gains in functional strength.

5.3 EMG Signal Analysis and Neuromuscular Adaptation

Electromyographic analysis provides insight into the underlying neuromuscular changes associated with rehabilitation. The EMG signals recorded during task execution reveal two key trends:

1. **Increased activation amplitude post-therapy:** The post-therapy EMG signals exhibit higher amplitude peaks, indicating stronger and more consistent muscle recruitment. This suggests improved voluntary activation and reduced neuromuscular inhibition.
2. **Reduced co-activation and signal variability:** Pre-therapy EMG patterns show irregular, noisy activation with evidence of co-contraction between antagonistic muscle groups. After therapy, the signals become more structured and task-specific, reflecting improved motor control and coordination.

The observed changes indicate that the AI-controlled glove not only assists movement mechanically but also facilitates neuroplastic adaptation, enabling more efficient muscle activation patterns. This is consistent with motor learning principles, where repetitive, assisted movement leads to reorganization of neural pathways (Figure 7).

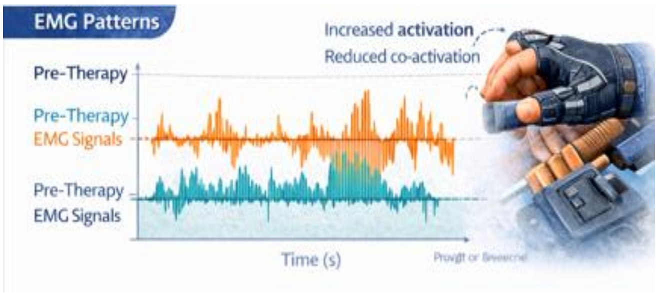

Figure 7: Impedance-based control for saf interaction

5.4 Range of Motion (ROM) Improvement

Range of motion was evaluated over the course of the 8-week therapy period, with results indicating a progressive and nonlinear improvement trajectory. The ROM increased from an initial value of approximately **20°–25°** to nearly **80°**, representing a gain of approximately **+60°** in joint mobility (Figure 8).

The improvement curve follows a typical rehabilitation profile:

- rapid initial gains during early adaptation,
- gradual saturation as physiological limits are approached.

This trend reflects both mechanical improvements in joint flexibility and neuromuscular adaptation enabling greater voluntary movement.

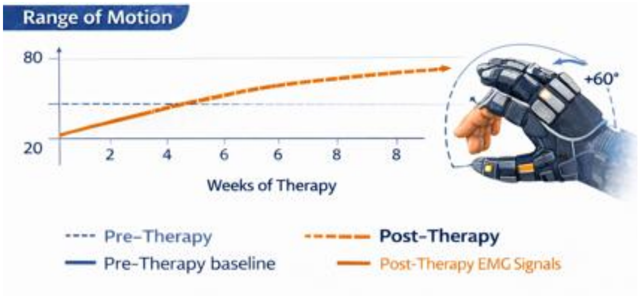

Figure 8: Range of motion analysis

The ability to achieve a larger ROM is critical for functional recovery, as it directly influences the range of tasks the patient can perform. The results demonstrate that the glove effectively facilitates both **passive stretching** and **active movement recovery**.

5.5 Integrated Performance Analysis

When considered together, the three evaluation domains reveal a consistent pattern of improvement:

- **Strength (Grasp Performance):** significant increases in both power and precision grip
- **Control (EMG Patterns):** more efficient and coordinated muscle activation
- **Mobility (ROM):** substantial expansion of achievable joint angles

Importantly, these improvements are interdependent. Enhanced ROM enables better grasp execution, while improved EMG patterns contribute to more efficient force generation. The AI control system acts as a unifying component, continuously adapting assistance to optimize all three aspects simultaneously.

5.6 Discussion of Results

The experimental results validate the effectiveness of integrating artificial intelligence into rehabilitation glove control. The assist-as-needed paradigm ensures that patients remain actively engaged, which is critical for motor learning. At the same time, the system compensates for deficits, enabling successful task completion and reinforcing correct movement patterns.

The observed improvements in EMG signals further suggest that the system promotes **neuromuscular re-education**, rather than merely providing mechanical assistance. This distinction is crucial, as long-term recovery depends on restoring voluntary control rather than relying on external support.

However, it should be noted that variability between patients, sensor noise, and differences in initial impairment levels can influence outcomes. Future studies should include larger cohorts and standardized clinical scales to further validate these findings.

VI. DISCUSSION

The results indicate that integrating artificial intelligence into the control of an actuated rehabilitation glove leads to meaningful improvements in hand function. Notable gains were observed in grasp strength, electromyographic activity, and range of motion, suggesting that the system effectively supports both mechanical assistance and neuromuscular recovery.

The increase in grasp and pinch strength reflects enhanced coordination and force generation across finger joints, particularly in tasks requiring fine motor control. Improvements in EMG patterns, characterized by higher activation and reduced co-contraction, indicate more efficient muscle recruitment and suggest underlying neuroplastic adaptation. Similarly, the progressive increase in range of motion demonstrates both improved joint flexibility and the recovery of voluntary movement capability [13-14].

A key factor contributing to these outcomes is the assist-as-needed control strategy. By adapting assistance in real time based on user effort, the system maintains active patient engagement while preventing over-reliance on robotic support. This balance is essential for promoting motor learning and long-term functional recovery.

Despite these promising findings, several limitations remain. Variability in EMG signals and nonlinear actuator behavior can affect control accuracy, while the reliance on data-driven models raises questions about robustness across diverse patient populations. Additionally, further validation using standardized clinical metrics and larger cohorts is necessary.

Overall, the results support the potential of AI-driven wearable robotics as an effective and scalable solution for hand rehabilitation, particularly in enabling personalized, adaptive therapy.

VII. CONCLUSION

AI-driven actuated gloves represent a significant advancement in hand rehabilitation technology. By combining wearable robotics with intelligent control, these systems provide adaptive, patient-specific therapy that evolves with recovery progress. The integration of machine learning and reinforcement learning enables precise assistance, improved engagement, and enhanced therapeutic outcomes. Continued research will further bridge the gap between clinical needs and intelligent rehabilitation systems.

REFERENCES

[1] H. I. Krebs, N. Hogan, "Robotic therapy: The tipping point," *IEEE Spectrum*, 2012.

[2] D. J. Reinkensmeyer *et al.*, "Robotics, motor learning, and neurologic recovery," *Annual Review of Biomedical Engineering*, 2016.

[3] H. In *et al.*, "Exo-Glove: A wearable robot for hand rehabilitation," *IEEE Robotics & Automation Magazine*, 2015.

[4] S. Polygerinos et al., "Soft robotic glove for hand rehabilitation and task-specific training," *IEEE TNSRE*, 2015.

A. Yap *et al.*, "Design of soft robotic glove for hand rehabilitation," *IEEE ICRA*, 2016.

[5] S. Calinon, "Robot learning from demonstration in rehabilitation robotics," *Robotics and Autonomous Systems*, 2016.

[6] M. Atzori, H. Müller, "Control capabilities of EMG signals for hand prosthetics," *Frontiers in Neurorobotics*, 2015.

[7] D. Silver *et al.*, "Reinforcement learning: An introduction," *MIT Press*, 2018.

[8] N. Hogan, "Impedance control: An approach to manipulation," *ASME Journal of Dynamic Systems*, 1985.

[9] R. Riener *et al.*, "Patient-cooperative control strategies for robot-aided therapy," *IEEE TNSRE*, 2005.

[10] J. Mehrholz *et al.*, "Electromechanical-assisted training for arm rehabilitation after stroke," *Cochrane Database*, 2018.

[11] S. Balasubramanian *et al.*, "Motor learning principles for rehabilitation," *Journal of NeuroEngineering and Rehabilitation*, 2010.

[12] R. Colombo *et al.*, "Robotic techniques for upper limb evaluation and rehabilitation," *Neurorehabilitation and Neural Repair*, 2005.

[13] G. Kwakkel *et al.*, "Effects of robot-assisted therapy on recovery after stroke," *The Lancet Neurology*, 2008.

AUTHOR'S BIOGRAPHY

Zlata Jelačić is Associate Professor in Department of Mechanics at the Faculty of Mechanical Engineering, University of Sarajevo, Bosnia and Herzegovina. PhD thesis was in the field of rehabilitation robotics, namely the development of an active above-knee prosthesis with actuated knee and ankle joints.

Citation of this Article:

Zlata Jelačić. (2026). Artificial Intelligence in Control of an Actuated Glove for Hand Rehabilitation. *International Research Journal of Innovations in Engineering and Technology - IRJIET*, 10(4), 355-362. Article DOI https://doi.org/10.47001/IRJIET/2026.104050

****