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Review Article

Use of Artificial Intelligence Systems for Hand Motor Recovery in Stroke: A Narrative Review

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Abstract: With the global population aging rapidly, the incidence of stroke and its associated burden on healthcare systems and society are projected to rise significantly. Stroke survivors often experience a range of long-term complications, including sensory, motor, cognitive, and psychological impairments. Among these, upper limb dysfunction—particularly involving the hands—is a major barrier to performing essential activities of daily living (ADLs) in patients with hemiplegia. Consequently, restoring hand function has become a central focus in post-stroke rehabilitation. Motor recovery is often facilitated through compensatory methods, such as the use of robotic devices for hand therapy, which have seen notable development since the late 20th century. This review explored the current landscape of hand rehabilitation systems that incorporate hand motion recognition technologies, examining their technical approaches, strengths, and limitations. In addition, the role of artificial intelligence in enhancing the functionality and adaptability of these systems is discussed. The paper also outlines existing challenges and suggests directions for future research in the field.

1. Introduction

Stroke remains a leading cause of adult disability worldwide and is projected to become an even greater public health challenge in the coming decades due to the rapidly aging global population. According to the World Health Organization (WHO), approximately 15 million people suffer a stroke each year, with nearly 5 million left permanently disabled. While advancements in emergency medical care have significantly improved survival rates, many stroke survivors experience residual impairments that affect their independence and quality of life [1]. These impairments may include motor, sensory, cognitive, and psychological dysfunctions, with motor deficits—particularly in the upper limbs—being among the most common and debilitating [2].

Upper limb impairments, especially loss of fine motor control in the hand, present serious obstacles to performing activities of daily living (ADLs) such as eating, grooming, writing, and using tools [3]. Hemiplegia on one side of the body, is a frequent outcome of stroke and can severely limit hand function, reducing the ability to perform tasks that require dexterity and co-ordination [4]. Therefore, restoring hand function is a critical component of post-stroke rehabilitation and a major determinant of a patient's ability to regain independence [5].

Effective rehabilitation is critical for restoring motor function after stroke. Traditional rehabilitation methods often require intensive, repetitive therapy administered by trained professionals, posing challenges in terms of cost, accessibility, and patient adherence [6]. In recent decades, technological innovations have led to the development of robotic and sensor-based systems aimed at enhancing the effectiveness and efficiency of rehabilitation programs [7].

One promising area involves hand motion recognition technologies, which can accurately track hand movements and provide real-time feedback to guide therapy [8]. When integrated with robotic rehabilitation devices and enhanced by artificial intelligence (AI), these systems have the potential to personalize treatment, monitor progress, and optimize outcomes for patients. AI-driven approaches can further improve adaptability, automation, and data analysis, making rehabilitation more responsive to individual needs [9].

This paper presents a comprehensive review of the current state of hand function rehabilitation AI systems that utilize hand motion recognition technologies, with a particular focus on the integration of artificial intelligence [10]. It examines the advantages and limitations of existing systems, highlights the role of AI in improving rehabilitation outcomes, and discusses key challenges and future directions for research in this evolving field.

Inclusion Criteria:

- Population: Adult patients diagnosed with ischemic or haemorrhagic stroke, Patients presenting with upper extremity motor impairments due to stroke, Studies including chronic, sub-acute, or acute stroke phases.
- Interventions: Studies including Artificial intelligence-based rehabilitation for Hemiplegic patients
- Outcomes Measures: Functional outcomes using tools such as Fugl-Meyer Assessment (FMA), Wolf Motor Function Test (WMFT), Motor Assessment Scale (MAS), Action Research Arm Test (ARAT), or Activities of Daily Living (ADL) scales.
- Study Types: Randomized Controlled Trials (RCTs), comparative studies, and systematic reviews published in peer-reviewed journals, Studies published between 2000 and 2024.
- Language: Articles published in English.

Exclusion Criteria:

- Population: Studies involving patients with other neurological conditions (e.g. Parkinson's disease, multiple sclerosis) not specific to stroke, Studies involving paediatric or non-stroke-related upper extremity impairments.
- Interventions: Studies not including Artificial intelligence-based rehabilitation for hemiplegic patients or those interventions unrelated to the motor recovery of upper limbs (e.g., cognitive therapy, pharmacological interventions)

- Outcome Measures: Studies lacking quantitative assessment of upper limb function, studies not reporting pre- and post-intervention outcomes.
- Study Design: Case studies, editorials, letters to editors, abstracts without full-text availability, non-peer-reviewed articles or grey literature.
- Language: Studies published in languages other than English without available translation.

Hand Rehabilitation System Utilizing Gesture Recognition

Hand Rehabilitation System Utilizing Computer Vision Techniques

Hand gesture recognition using computer vision works by using cameras, like regular or depth cameras to capture images or videos of hand movements. These images are then analysed by advanced computer programs, often using deep learning (like CNNs), to recognize and understand the gestures.

One big advantage of this method is that users don't have to wear anything special, which makes it more comfortable and easier to set up. This makes it especially useful for hand therapy and rehabilitation.

However, there are some downsides. The system can be affected by lighting and background conditions, which may reduce how well it works. It may also not be as fast or accurate as some other methods. Sometimes, small markers might be needed on the hand to help the system track movements better.

Devices used for this kind of gesture recognition usually include RGB cameras (which capture colour images) and depth cameras (which measure distance). These systems are used in robotic rehab tools and therapy games to help improve hand function.

Virtual Environment-Assisted Hand Rehabilitation System

Virtual environment-based rehabilitation systems use immersive or semi-immersive digital simulations to support the recovery of hand function in patients, particularly those affected by stroke or other neurological conditions. These systems create interactive virtual spaces where patients can perform a variety of therapeutic exercises designed to improve motor control, co-ordination, and strength of the hand and fingers.

By leveraging technologies such as Virtual Reality (VR), Augmented Reality (AR), or Mixed Reality (MR), these systems provide real-time visual and sometimes haptic feedback, enhancing patient engagement and motivation during therapy sessions. Virtual environments enable the simulation of realistic or gamified scenarios that encourage repetitive practice—an essential factor in neural plasticity and motor learning.

One of the key advantages of virtual environment rehabilitation is the ability to tailor exercises to individual patient needs, allowing for adaptive difficulty levels and personalized therapy plans. This flexibility helps maintain patient interest and can improve adherence to rehabilitation programs. Moreover, virtual systems often incorporate precise tracking of hand movements through sensors or cameras, enabling accurate assessment of motor performance and progress monitoring.

Patients engage in therapeutic exercises within a virtual environment, interacting with digital objects using tracked hand movements captured by sensors such as data gloves, depth cameras (like Microsoft Kinect), or inertial measurement units (IMUs). The system provides real-time feedback—visual, auditory, and sometimes haptic—to reinforce proper movement and encourage repetition, which is critical for neuroplasticity and motor learning.

Subjects as a group improved in fractionation of the fingers, thumb and finger range of motion, and thumb and finger speed, retaining those gains at the 1-week retention test. Transfer of these improvements was demonstrated through changes in the Jebsen Test of Hand Function and a decrease after the therapy in the overall time from hand peak velocity to the moment when an object was lifted from the table.

Rehab Master- Rehab Master is a virtual reality rehabilitation platform that includes games aimed at upper limb and hand function recovery. It uses motion sensors and cameras to track patient movements, offering interactive tasks like virtual painting or playing musical instruments to engage patients in fine motor exercises.

Amadeo by Tyro motion- Although primarily a robotic device, Amadeo integrates virtual environments to facilitate hand therapy. It allows patients to control virtual tasks using robotic assistance, providing visual feedback and adapting therapy to the user's ability level.

Music Glove- This system pairs a sensor-equipped glove with computer-based music games. Patients practice finger and hand movements by playing virtual instruments, promoting fine motor skill improvement through engaging and rhythmic gameplay.

Virtual Rehab by Gesture Tek- A fully immersive VR platform that uses motion capture technology to enable patients to interact with virtual objects through natural hand gestures. It offers a range of customizable exercises for hand rehabilitation with real-time feedback and progress tracking.

Sr.No.	Device- Gesture Recognition	Key Functional Improvements
1.	Laver K.E., published a study on Rehab Master device	Fine motor skill development -Improved coordination and range of motion - Enhanced patient engagement
2.	Loredana Raciti, published a study on, Amadeo by Tyro motion device	-Muscle re-education - Improved movement in severely impaired hands - Gradual functional gain
3.	Vatsal Shah and Miguel Cuen, published a study on Music Glove device	- Improved finger dexterity - Enhanced hand strength and movement timing - Promotes neuroplasticity through rhythm
4.	Yuexing Gu, published a study on Virtual Rehab (Gesture Tek) device	-Functional hand use through gesture control -Increased range of motion and control - Personalized exercise programs

Computer Vision-Driven Robotic Device for Hand Therapy

Hand rehabilitation robots integrated with computer vision technology represent a cutting-edge solution in the field of neurorehabilitation. These systems assist patients suffering from hand motor impairments—often caused by stroke, spinal cord injury, or neurological disorders—by combining robotic actuation with vision-based movement analysis to deliver precise, adaptive therapy.

Computer vision technology involves using cameras (such as RGB, depth, or infrared sensors) to capture real-time images or video of the patient's hand movements. Advanced image processing algorithms—including deep learning, pose estimation, and motion tracking—analyse these images to interpret hand gestures, finger positions, and movement trajectories without requiring the patient to wear cumbersome gloves or markers.

The rehabilitation robot uses this visual feedback to provide appropriate assistance, resistance, or guidance during therapeutic exercises. For example, the robot may support finger extension while encouraging voluntary movement, helping to rebuild strength and co-ordination. The continuous monitoring and feedback loop enhances the therapeutic responsiveness and effectiveness.

Dexmo Exoskeleton Glove-Although primarily a haptic device, Dexmo integrates computer vision for precise hand motion tracking. It assists patients in performing hand movements by providing force feedback while monitoring their gestures visually. This enhances the quality of rehabilitation exercises.

Handy Rehab System-This system uses RGB-D cameras (such as Microsoft Kinect) to capture hand movements and a robotic exoskeleton to assist hand function recovery. The robot adapts its support based on visual tracking of finger flexion and extension during therapy.

RAPAEL Smart Glove-The Rapael system incorporates sensors and vision technology to track fine hand movements. It combines robotic assistance with visual motion capture to enable interactive rehabilitation games that promote hand function recovery.

Vision-Guided Soft Robotics-Some research prototypes combine soft robotic gloves with computer vision to assist hand rehabilitation. Cameras track the hand's position and guide the soft robot's actuation, providing a flexible and comfortable therapy option.

Sr. No.	Device Computer Vision-Driven Robotic Device	Primary Targeted Functions	Additional Functions achieved.
1.	Manuel Caeiro-Rodríguez, published a study using, Dexmo Exoskeleton Glove device.	Tactile perception, grip strength, motor control	Virtual reality interaction, haptic feedback, proprioception
2.	Yuanjing Xu, published a study using, Handy Rehab System	Finger flexion/extension, wrist mobility, functional reach	Adaptive robotic assistance, marker less tracking, portability
3.	Seyoung Shin, published a study using, RAPAEL Smart Glove	Finger flexion/extension, wrist flexion/extension, forearm supination/pronation, wrist deviation	Cognitive engagement through gamified exercises, real-time feedback, neuroplasticity stimulation
4.	Hong Kai Yap, published a study using, Vision-Guided Soft Robotic Gloves	Finger and wrist movement, comfort and compliance, real-time feedback	Soft robotic actuation, telehealth integration, wearable convenience

Wearable Technology for Hand Function Rehabilitation

Gesture recognition using wearable devices involves users wearing equipment such as gloves, rings, bracelets, wristbands, or armbands that are embedded with sensors to capture motion data or physiological signals related to hand movements. This approach enables the recognition of a wide range of gestures using relatively small input data while maintaining high accuracy. It can detect hand movements and three-dimensional spatial information in real-time. The system is robust and less susceptible to external disturbances; however, it tends to be costly. Wearing such devices may sometimes hinder the therapist's movements, and factors like sweating can impact accuracy. Additionally, prolonged use can cause fatigue, and devices often require calibration before each session. Based on the type of data gathered, wearable devices are categorized into physiological signal sensors, kinematic signal sensors, optical signal sensors, among others. In practice, multiple types of sensors are often combined to provide multimodal data input. The gestures detected through wearable devices can serve as control commands for hand rehabilitation robots, enabling active training of hand functions. Furthermore, these devices can assist in evaluating a patient's progress during rehabilitation.

Physiological Sensor-Driven Hand Function Recovery Robot

This type of rehabilitation robot is designed to assist patients in recovering hand function by leveraging physiological signals collected through various sensors. Physiological signals, such as electromyography (EMG), electroencephalography (EEG), or bioelectrical signals, reflect the user's muscle activity, nerve impulses, or brain signals related to hand movements. By interpreting these signals, the robot can accurately understand the user's intended hand motions, even when voluntary movement is weak or impaired.

The robot typically integrates wearable physiological signal sensors that detect subtle bioelectrical changes generated during muscle contraction or brain activity. These signals are processed in real-time to control the robot's actuators, which guide the hand through specific therapeutic exercises. This biofeedback mechanism allows for active participation from the patient, promoting neuroplasticity and accelerating functional recovery.

Key advantages of this approach include precise intention recognition, enabling customized therapy tailored to the patient's current motor ability. It also allows for continuous monitoring of muscle activation patterns and progress evaluation. Furthermore, by enabling hands-free or minimal-effort control, this robot reduces patient fatigue and enhances motivation during rehabilitation sessions.

However, challenges such as signal noise, sensor placement accuracy, and individual variability in physiological signals require advanced signal processing algorithms and careful calibration. Overall, physiological signal sensor-based hand rehabilitation robots represent a promising technology in neurorehabilitation, offering an intuitive, responsive, and effective way to restore hand function.

Kinematic Sensor-Driven Hand Function Recovery Robot

A kinematics sensor-based hand function rehabilitation robot is designed to assist patients in regaining hand mobility and dexterity by using sensors that capture the motion and position of the hand and fingers. Kinematic sensors, such as accelerometers, gyroscopes, magnetometers, or motion capture devices, measure parameters like joint angles, velocity, acceleration, and spatial orientation during hand movements.

These sensors provide real-time data on the user's hand posture and movement dynamics, which the rehabilitation robot uses to deliver precise, adaptive therapy. By continuously tracking the range of motion and movement patterns, the robot can guide the patient through customized exercises that target specific motor impairments. This enables the robot to support both passive movements—where the robot moves the patient's hand—and active movements—where the patient initiates motion with robotic assistance.

The integration of kinematic sensors enhances the system's ability to evaluate progress objectively and adjust therapy intensity based on real-time feedback. This data-driven approach facilitates personalized rehabilitation plans that can adapt as the patient's hand function improves.

One of the main benefits of using kinematics sensors is their high accuracy in capturing complex hand motions without invasive procedures. They also allow for continuous monitoring without interfering significantly with natural movement. However, challenges such as sensor drift, calibration requirements, and sensitivity to external magnetic fields must be managed through advanced signal processing and sensor fusion techniques.

Overall, kinematics sensor-based hand rehabilitation robots offer a promising solution for restoring hand function by providing precise motion tracking, enabling interactive therapy, and supporting detailed assessment throughout the recovery process.

Optical Sensor-Driven Hand Function Recovery Robot

An optical sensor-based hand function rehabilitation robot uses vision-based technologies to assist patients in recovering hand mobility and dexterity. Optical sensors typically include cameras, infrared sensors, depth sensors, or structured light systems that capture detailed visual information about hand movements in three-dimensional space.

These sensors track the position, orientation, and motion of the hand and fingers without requiring the patient to wear any physical device, offering a non-invasive and comfortable rehabilitation experience. The collected data enables the robot to analyse the user's hand gestures, movement range, and co-ordination in real-time.

By processing this visual information, the rehabilitation robot can provide interactive and adaptive therapy tailored to the patient's specific needs. It can guide exercises, offer immediate feedback, and adjust difficulty levels based on the patient's performance. Additionally, the system can continuously monitor progress, helping therapists to evaluate improvements objectively.

Optical sensor-based systems are valued for their high spatial resolution and ability to capture complex hand gestures accurately. However, they can be sensitive to environmental factors such as lighting conditions and occlusions (when parts of the hand are blocked from view), which may affect tracking accuracy. To overcome these challenges, advanced image processing and machine learning algorithms are often employed.

Overall, optical sensor-based hand rehabilitation robots present a promising approach by combining precise motion tracking with user-friendly, contactless operation, thereby enhancing the effectiveness and accessibility of hand function rehabilitation.

Sr.No.	Device-Wearable Technology	Key Functional Improvement
1.	Wearable Technology (General) (gloves, armbands, wristbands, etc.)	- Hand movement accuracy - Spatial awareness and 3D hand control - Motor planning and coordination - Active engagement in therapy
2.	Physiological Sensor-Driven Robot	- Voluntary muscle activation (even in weak muscles)

	(e.g., EMG, EEG-based systems)	- Neural reactivation and motor relearning - Customized exercise based on brain/muscle activity - Neuroplasticity stimulation
3.	Kinematic Sensor-Driven Robot (e.g., accelerometers, gyroscopes)	- Range of motion (ROM) - Hand and finger coordination - Speed and smoothness of movement - Functional task training (e.g., grasping)
4.	Optical Sensor-Driven Robot (e.g., camera, infrared, depth sensors)	- Fine motor skills - Gesture control and spatial orientation - Real-time motion correction and feedback - Comfortable, non-restrictive therapy

2. Artificial Intelligence in Assistive Robotic Devices for Hand Therapy

In addition to ongoing research focused on the hardware components for recognizing hand movements, effective hand rehabilitation robots also demand advancements in software development. Achieving true intelligence in these systems requires seamless integration of both hardware and software. With the rapid progress in artificial intelligence (AI), numerous innovative applications and technologies have emerged. AI can be integrated into multiple functional areas of hand rehabilitation robots, including motion detection, robotic control, human-machine collaboration, interactive game environments, personalized training program design, performance evaluation, cloud-based data platforms, as well as structural optimization of the robotic systems. However, in real-world applications, the implementation and research of AI in hand rehabilitation robots remain limited or insufficiently developed—largely due to technological challenges and the lack of widespread availability of supporting medical infrastructure.

2.1. Gesture Analysis Method

In hand rehabilitation robots, real-time recognition of isolated dynamic gestures is essential for accurate motion interpretation and patient interaction. Artificial intelligence (AI) algorithms are commonly employed to enable this capability. The fundamental approach involves training a model using a dataset of gesture samples, and then applying the trained model to classify or predict incoming gesture data in real-time.

Several widely adopted AI techniques used for gesture recognition include Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks.

For instance, Zhang Guangxing from Qingdao University of Science and Technology developed a wrist rehabilitation robot based on the LDA algorithm, which successfully recognized five different hand movements with an accuracy rate exceeding 90%. Similarly, Zhang Fahui from Nanchang University utilized an SVM-based model to identify four gesture types, achieving an impressive average accuracy of 99.3%. Liu Wei, from Nanjing University of Aeronautics and Astronautics, implemented a CNN-driven hand exoskeleton robot that could detect four kinds of gestures with an accuracy of 96.18%. Additionally, Zhang Jianxi designed a hand rehabilitation system that integrated both RNN and LSTM models to recognize nine different gestures, reaching an average accuracy of 91.44%.

2.2. Control of the Hand Rehabilitation Robot

Safety issues need to be addressed in the control strategy or algorithm of the hand rehabilitation robot. More precise control strategies are needed, as well as balancing the ratio between the degree of control the robot has over the hand and the risk of miscalculation. For example, Jun Wu designed a pneumatic flexible hand rehabilitation robot, used a sliding mode control algorithm based on fuzzy compensation to control the pneumatic muscles, proposed a dynamic surface control based on a nonlinear interference observer to realize the control of the pneumatic muscle system, and used an echo state network (ESN) with recursive least squares (RLS) for PID parallel adaptive control. Yihao Du et al. proposed an adaptive control strategy based on a variable impedance equation model, which can combine the desired trajectory identified by physiological signals to obtain the final trajectory and calculate the required motion of each joint of the rehabilitation robot. Yonghao Yin from Yanshan University also used RBF neural networks to approximate the compensation of errors caused by external perturbations and uncertainties to control the rehabilitation robot to achieve the desired results.

2.3. Human-Robot Intelligence Collaboration

Artificial intelligence can also be applied to the human-robot collaboration of hand rehabilitation robots, mainly in the assisted training mode. For example, Wang Xiangyu from Harbin Institute of Technology designed an impedance control system to carry out motion following the hand rehabilitation robot in the assisted mode, which can identify the bending angle and muscle strength of the patient’s fingers when the patient’s hand has a certain behavioural ability and apply the appropriate force to help the patient complete the movement, and the system uses a fuzzy neural network.

2.4. Interactive Game Design

In order to increase patients’ interest and motivation during rehabilitation training, the hand rehabilitation robot can be equipped with some interactive games, such as interactive control based on voice recognition, virtual reality games based on visual recognition, and games based on brain–computer interface, etc. Artificial intelligence is also applied here. For example, Zhu Xikun from Zhengzhou University designed a finger rehabilitation training system that can interact with active modes through both gesture recognition and voice recognition using algorithms such as neural networks and hidden Markov models. Cao Yali designed a hand function rehabilitation robot software system that uses Unity3D to design different virtual games for different training modalities. Mou Yang et al. designed an Android-based portable virtual reality rehabilitation device that can be applied to a hand rehabilitation robot. Ying Zhang from Beijing University of Posts and Telecommunications designed a monocular vision-based hand grasping interaction training module.

Sr. No.	Artificial Intelligence in Assistive Robotic Devices	Key Functional Improvement
1.	Gesture Analysis Method	- Gesture control and fine motor precision - Improved response time and hand-eye coordination - Cognitive-motor integration
2.	Control of Hand Rehabilitation Robot	- Muscle strength adaptation - Safe movement execution

		- Improved range of motion and motor control
3.	Human robot intelligence collaboration	- Active participation in movement - Enhanced motor relearning - Reduced compensation habits
4,	Interactive Game Design	- Increased motivation and engagement - Improved reaction speed and attention - Hand-eye coordination

3. Discussion

3.1. Challenges and Future Directions of the Current Research

The preceding discussion has explored both the hardware and software aspects of current developments in hand function rehabilitation robots. However, several limitations remain that require further investigation and refinement in future work. Below is a summary of key challenges identified in existing studies:

- Limitations of Vision-Based Hand Rehabilitation Devices Hand rehabilitation systems that rely on computer vision technologies can often be bulky and inconvenient, especially when they require the attachment of physical markers. These systems may lack portability and user comfort, particularly in outdoor or non-clinical environments. Some users may even experience dizziness due to prolonged visual engagement. In monocular vision systems, recognition performance is susceptible to variations in lighting, background color, and skin tone. While binocular vision can alleviate some of these issues, it introduces increased complexity in terms of calibration and image correction, resulting in higher computational demands and potential degradation in image quality. Ongoing improvements in both hardware design and algorithm efficiency are essential to address these limitations.
- Lack of Tactile Feedback in Virtual Training Environments In gesture recognition systems that use computer vision for bare-hand tracking—especially those integrated with interactive games for rehabilitative training—tactile feedback is often missing. This absence can reduce the effectiveness of therapy by failing to simulate real-world touch sensations, which are important for motor recovery. Additionally, key physical parameters such as movement angles and time duration are frequently overlooked, limiting the precision and therapeutic value of the training exercises.
- Limited Data Types in Vision-Based Gesture Recognition When using computer vision alone for gesture detection and rehabilitation training, the input data remains relatively basic. This simplicity can hinder the accurate recognition of complex gestures, often resulting in incomplete or imprecise data capture. To overcome these limitations, integrating additional information sources—such as physiological signals—can enable multi-modal data fusion, thereby enhancing the system's recognition accuracy and robustness.
- Challenges of Wearable Sensor-Based Gesture Recognition Hand rehabilitation robots that rely on wearable sensors for gesture recognition typically require users to wear multiple external devices. This not only raises the overall cost but also reduces user convenience, presenting challenges particularly for elderly or physically limited patients. Furthermore, these systems place high demands on the processing power and algorithmic efficiency of the wearable hardware, which may result in delays or latency. Additionally, if the sensor placement changes, the gesture recognition algorithm often needs to be retrained, reducing scalability. Achieving a balance among comfort, sensor diversity, stability, accurac’y, and real-time performance remains a key area for future optimization. Unsupervised use also brings up concerns around safety and reliability.
- Limitations of Physiological Signal-Based Gesture Recognition Robots that use physiological signals—such as EMG (electromyography)—for gesture detection often face signal instability during acquisition and transmission. These systems also tend to support a limited range of gestures, making it difficult to support fine finger movements or recognize continuous motion sequences. To improve performance in this area, multi-modal control approaches can be adopted, incorporating kinematic data, optical inputs, and other complementary signals to strengthen recognition capabilities.
- Lack of Closed-Loop Control Systems Regardless of the specific technology used, effective hand rehabilitation robots should be built around closed-loop control mechanisms. These systems rely on real-time sensor feedback—such as force, angle, position, and haptic responses—to adaptively adjust the robot’s

output based on the patient's current status. Incorporating such feedback loops ensures more responsive, personalized, and safe rehabilitation sessions.

- Low Technology Readiness of Vision-Based Rehabilitation Robots Currently, most hand function rehabilitation robots remain at the experimental or developmental stages. Systems that rely on computer vision in particular lag behind those based on wearable sensors in terms of practical deployment. According to the Technology Readiness Level (TRL) framework developed by Mankins, most vision-based rehabilitation systems are at TRL 5 or 6 (technology validation in relevant environments), with a small number reaching TRL 7 or 8 (system prototype demonstration). Very few have attained TRL 9, which indicates readiness for full-scale deployment and operational use. In contrast, many wearable sensor-based systems have already reached TRL 9, and most fall within TRL 5 to 7, highlighting their more advanced state of development and real-world applicability.

In addition to the challenges mentioned above, the clinical value of hand function rehabilitation robots has been assessed based on three key factors: appropriateness, acceptability, and practicality. Most well-established robotic rehabilitation systems have demonstrated strong appropriateness, whereas systems still under development generally show potential but remain less validated in clinical settings. Users' acceptance of these robots and vision-based training games often correlates with the perceived effectiveness of the therapy. While some users reported that game-based exercises enhanced their engagement and motivation, others raised concerns regarding aspects like comfort and wearability. In terms of practical application, many rehabilitation robots perform well in terms of functionality and adaptability. However, certain technical limitations still negatively impact the overall user experience. Improvements are still needed in areas such as the variety of functions and ergonomic design for enhanced wearing comfort. When robotic therapy is used in subacute/chronic phases, it yields notably superior improvements in motor scales, movement speed, and ADL independence—compared to conventional or mirror-only therapy. In acute stroke, short-term robotic intervention doesn't outperform standard rehab—but still shows motor gains.

In conclusion, both wearable devices and Computer Vision-Driven Robotic and Gesture Analysis methods offer valuable support in stroke rehabilitation, each with their own strengths. While vision-based systems provide detailed motion tracking and advanced gesture analysis, wearable devices offer greater portability, ease of use, and consistent real-time feedback, making them particularly effective in everyday rehabilitation settings. Their ability to function independently of external conditions like lighting or camera placement enhances their reliability and accessibility. Thus, while both approaches contribute meaningfully to recovery, wearable devices offer a more practical and user-friendly solution for continuous stroke rehabilitation.

Looking ahead, an ideal hand rehabilitation robot should be capable of replicating the therapeutic techniques of human physiotherapists, achieving true human–robot integration. It should also be upgradeable to allow clinician-guided assessment, personalized training program generation, and automated evaluation of rehabilitation outcomes.

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References

[1] Lin, Q.; Li, X.; Cheng, K.; Cheng, A.; Yu, C.; Zhou, Y. Effects of early cognitive rehabilitation training on cognitive function, motor function and activities of daily living in patients with stroke. *Chin. J. Rehabil. Med.* **2015**, *30*(3).

[2] Wang, J. Effects of finger flexion movement combined with comprehensive rehabilitation training on finger range of motion and upper limb function in patients with hemiplegia after stroke. *Chin. Gen. Pract.* **2017**, *20*(3).
[3] Chang, Y.; Meng, Q.; Yu, H. Research progress of hand rehabilitation robot technology. *Beijing Biomed. Eng.* **2018**, *37*(7).
[4] Leonardis, D.; Barsotti, M.; Loconsole, C.; Solazzi, M.; Troncossi, M.; Mazzotti, C.; Castelli, V.P.; Procopio, C.; Lamola, G.; Lamola, C.; et al. An EMG-controlled robotic hand exoskeleton for bilateral rehabilitation. *IEEE Trans. Haptics* **2015**, *8*, 140–151.
[5] Xiao, X.; Xiao, Y. *Rehabilitation Engineering Technology*; Huazhong University of Science and Technology Press: Wuhan, China, **2019**; pp. 367–371.
[6] Saa, A.; Aab, A.; Dsk, A. Effectiveness of an intensive, functional, gamified rehabilitation program in improving upper limb motor function in people with stroke: A protocol of the EnteRtain randomized clinical trial. *Contemp. Clin. Trials* **2021**, *105*, 106381.
[7] Yu, H. Rehabilitation robots: Ten visionary perspectives for the future. *Chin. J. Rehabil. Med.* **2020**, *35*(3).
[8] Vélez-Guerrero, M.; Callejas-Cuervo, M.; Mazzoleni, S. Artificial intelligence-based wearable robotic exoskeletons for upper limb rehabilitation: A review. *Sensors* **2021**, *21*, 2146.
[9] Harley, L.; Robertson, S.; Gandy, M.; Harbert, S.; Britton, D. The design of an interactive stroke rehabilitation gaming system. In *International Conference on Human-Computer Interaction*; Springer: Berlin/Heidelberg, Germany, **2011**.
[10] Merians, A.S. Sensorimotor training in a virtual reality environment: Does it improve functional recovery poststroke? *Neurorehabil. Neural Repair* **2006**, *20*, 252–267.
[11] Akn, A.; Atar, E.; Koyiit, H.; Tosun, A.; Kocyi, H. Effects of Kinect-based virtual reality game training on upper extremity motor recovery in chronic stroke. *Somatosens. Mot. Res.* **2018**, *35*, 25–32.
[12] Laver, K.E.; Lange, B.; George, S.; Deutsch, E.J.; Saposnik, G. Virtual reality for stroke rehabilitation. *Cochrane Database Syst. Rev.* **2011**, *2*, CD008349.
[13] Domínguez-Téllez, P.; Moral-Muñoz, J.; Salazar, A.; Casado-Fernández, E.; Lucena-Antón, D. Game-based virtual reality interventions to improve upper limb motor function and quality of life after stroke: Systematic review and meta-analysis. *Games Health J.* **2019**, *9*(1).
[14] Karamians, R.; Proffitt, R.; Kline, D.; Gauthier, L. Effectiveness of virtual reality- and gaming-based interventions for upper extremity rehabilitation poststroke: A meta-analysis. *Arch. Phys. Med. Rehabil.* **2020**, *101*, 885–896.
[15] Ain, Q.; Khan, S.; Ilyas, S.; Yaseen, A.; Tariq, I.; Liu, T.; Wang, J. Additional effects of Xbox Kinect training on upper limb function in chronic stroke patients: A randomized control trial. *Healthcare* **2021**, *9*, 242.
[16] Rizzo, A.; Kim, G. SWOT analysis of the field of virtual reality rehabilitation and therapy. *Presence* **2005**, *14*, 119–146.
[17] Mousavi Hondori, H.; Khademi, M.; Dodakian, L.; Cramer, S.C.; Lopes, C.V. A spatial augmented reality rehab system for post-stroke hand rehabilitation. *Stud. Health Technol. Inform.* **2013**, *184*, 279–285.
[18] Wang, Z.; Wang, P.; Xing, L.; Mei, L.; Zhao, J.; Zhang, T. Leap Motion-based virtual reality training for improving motor functional recovery of upper limbs and neural reorganization in subacute stroke patients. *Neural Regen. Res.* **2017**, *12*, 1823–1831.
[19] Alimanova, M.; Borambayeva, S.; Kozhamzharova, D.; Kurmangaiyeva, N.; Ospanova, D.; Tyulepberdinova, G.; Gaziz, G.; Kassenkhan, A. Gamification of hand rehabilitation process using virtual reality tools: Using Leap Motion for hand rehabilitation. In *Proceedings of the 2017 First IEEE International Conference on Robotic Computing (IRC)*, Taichung, Taiwan, 10–12 April 2017.
[20] Mukai, H.; Yamabe, K.; Abe, I.; Kikuchi, T.; Ohno, T. Development of rehabilitation robot for hand “ReRoH” for hemiplegic patients. In *Proceedings of the JSME Annual Conference on Robotics and Mechatronics (Robomec)*, Tokyo, Japan, 10–13 May 2017; pp. 2063–2068.