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Design and Experimental Validation of an AR-Enhanced Upper Limb Rehabilitation Robot with Adaptive Trajectory Control

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Abstract

Upper limb motor dysfunction caused by stroke, traumatic brain injury, and other neurological disorders has become a major global public health challenge, imposing heavy burdens on both healthcare systems and patient families. Conventional manual rehabilitation therapy is limited by insufficient therapist resources, inconsistent treatment quality, and a lack of quantitative evaluation, while most existing rehabilitation robots suffer from low terminal accuracy, poor adaptability to individual patient status, and low long-term training compliance. This paper presents a hybrid parallel-serial upper limb rehabilitation robot integrating multi-modal force-tactile perception, intelligent adaptive trajectory control, and immersive augmented reality (AR) interaction. First, a multi-body dynamic model of the hybrid mechanism is established based on the Lagrangian method, and a domestically manufactured hardware platform is developed with 100% localization rate of core components, achieving 0.1 mm terminal repeat positioning accuracy. Second, a multi-modal sensing fusion framework combining surface electromyography (sEMG), 3D force signals, and kinematic data is constructed; an optimized BiLSTM-Attention model with reinforcement learning is proposed to predict patient motion intention 300 ms in advance, and dynamically adjust auxiliary torque and motion trajectory with a control response delay ≤ 30 ms. Third, a lightweight asynchronous AR training system is developed to realize haptic-visual synchronous feedback, with interaction latency controlled within 50 ms. Bench tests and preliminary clinical validation show that the proposed robot outperforms industry average levels in core performance indicators, increases patients' active motion induction rate by 30%, and shortens the Brunnstrom stage progression cycle by approximately 40% compared with traditional manual training. This system provides a precise, intelligent, and patient-friendly solution for upper limb motor rehabilitation, with broad clinical application prospects.

Keywords

Upper Limb Rehabilitation Robot, Hybrid Parallel-Serial Mechanism, Adaptive Trajectory Control, Multi-Modal Sensing, Augmented Reality, Force-Tactile Perception

1. Introduction

With the aging of the global population and the rising incidence of cerebrovascular diseases, the number of patients with upper limb motor dysfunction continues to grow rapidly. Statistics show that 70% - 80% of stroke survivors suffer from upper limb motor impairment, which severely reduces their ability to perform activities of daily living (ADL) [1] [2]. Clinical evidence indicates that high-intensity, repetitive, and task-oriented rehabilitation training can effectively promote neural plasticity and improve motor function [3]. However, traditional one-to-one manual rehabilitation relies heavily on the experience of therapists, suffers from uneven treatment quality, and fails to meet the growing demand for long-term, standardized rehabilitation [4].

In recent years, upper limb rehabilitation robots have become a research hotspot in the field of rehabilitation engineering. Existing products can be divided into two categories: imported high-end devices represented by MIT-MANUS and InMotion Arm, which have stable performance but extremely high cost and low penetration in primary medical institutions; and domestic devices, which generally have shortcomings such as insufficient terminal control accuracy, weak adaptive adjustment ability, and a single interaction mode. Most existing robots follow fixed preset trajectories, cannot dynamically adjust training strategies based on patients' real-time muscle status and motor intentions, and lack immersive interactive experiences, resulting in low patient compliance and limited rehabilitation effects [5].

To address the above problems, this paper develops an AR-enhanced upper limb rehabilitation robot with adaptive trajectory control capability. The main contributions are as follows:

1) A hybrid parallel-serial mechanical structure is designed, which combines the advantages of the large working space of serial mechanisms and high rigidity and precision of parallel mechanisms, and realizes 100% localization of core components.

2) A multi-modal sensing fusion adaptive control strategy is proposed, which integrates sEMG, force, and kinematic signals to realize real-time motion intention recognition and dynamic trajectory adjustment.

3) An immersive AR interactive training system with a lightweight asynchronous

architecture is built to realize haptic-visual synchronous feedback and improve patient training compliance.

4) Systematic bench tests and preliminary clinical verification are carried out to prove the advanced performance and clinical application value of the system.

2. Mechanical System Design of the Rehabilitation Robot

2.1. Overall Architecture of the Hybrid Parallel-Serial Mechanism

Addressing the contradiction between the working space and terminal accuracy of traditional rehabilitation robots [6], this study adopts a hybrid parallel-serial mechanism design. The shoulder joint part adopts a parallel closed-chain structure to ensure high rigidity and high-precision control, while the elbow-wrist extension part adopts a series structure to expand the working range of motion, which fully matches the motion characteristics of human upper limb shoulder-elbow-wrist multi-joint synergy.

The mechanism has 4 degrees of freedom, encompassing the primary motion modes required for upper-limb rehabilitation: shoulder flexion/extension, shoulder abduction/adduction, elbow flexion/extension, and forearm pronation/supination. The modular design of the end effector enables quick replacement of different grips to accommodate patients with varying hand function levels. The overall structure, key components, workspace simulation, and clinical application form of the developed rehabilitation robot are shown in **Figure 1**.

2.2. Kinematic and Dynamic Modeling

Based on the Denavit-Hartenberg (D-H) parameter method, the hybrid parallel-serial mechanism is equivalent to a unified serial system, and the inverse kinematics solution model of the robot is established to accurately calculate the drive position of each joint corresponding to the target pose of the end effector. The core inverse kinematics algorithm adopted in this study has been authorized as a national invention patent [7].

For the nonlinear, complex, closed-chain characteristics of the parallel mechanism [8], a multi-rigid-body dynamic equation is established using the Lagrangian method, and a dynamic simulation process compatible with multiple drive modes is constructed. The dynamic characteristics of the mechanism under different training modes are analyzed from the dimensions of time-domain dynamic response, trajectory tracking error, and system dynamic stress [9], which provides a theoretical basis for hardware design and control algorithm optimization.

2.3. Localized Hardware Implementation

To break the dependence on imported core components and reduce the overall cost of the machine, all core components, such as servo motors, precision reducers, and multi-dimensional force sensors, are sourced from domestically produced, mature industrial-grade devices, and the localization rate of core functional components reaches 100%. Through mechanism topology optimization and component

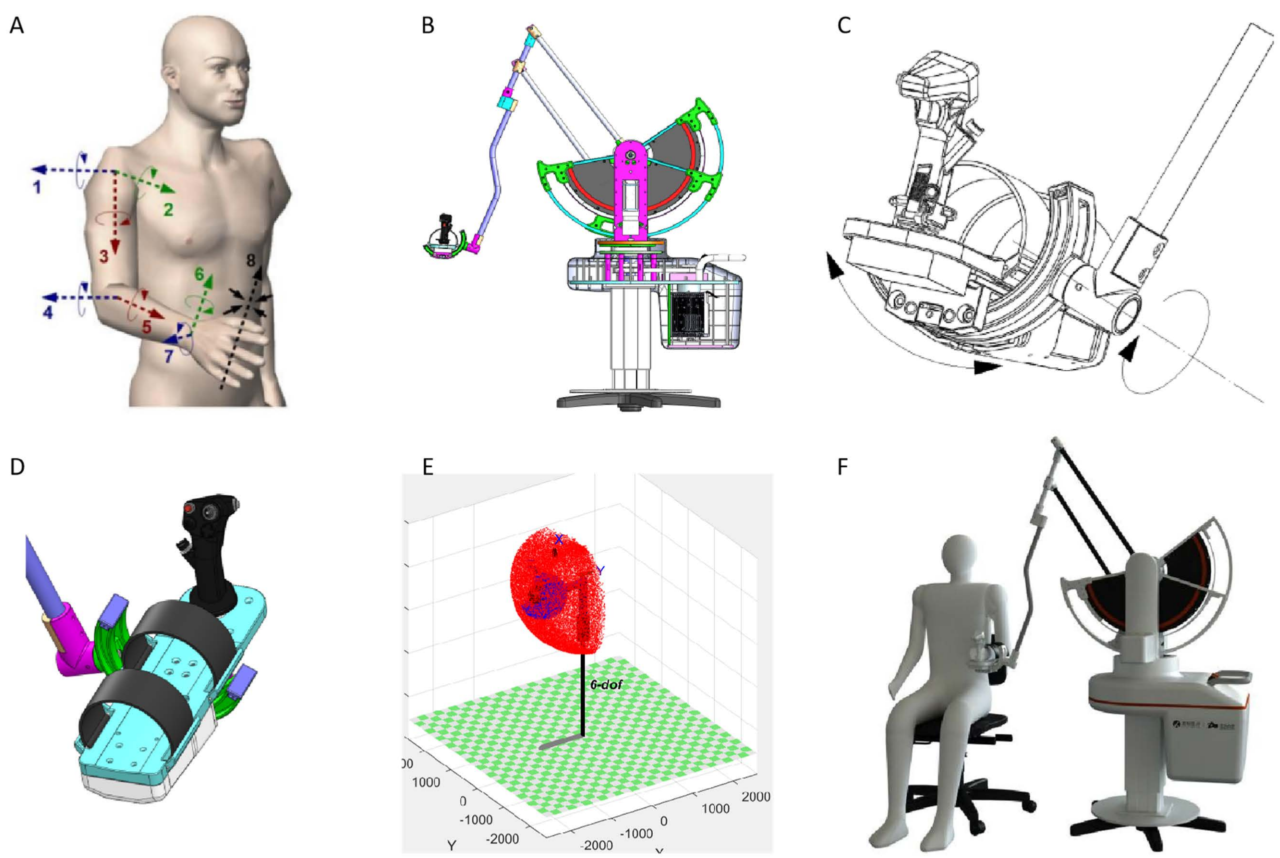

Figure 1. Simulation and structural overview of the developed AR-enhanced intelligent upper limb rehabilitation robot. (A) Schematic illustration of human upper limb motion degrees of freedom for kinematic parameter matching; (B) Full 3D simulation model of the robot's hybrid parallel-serial mechanical architecture; (C) Detailed mechanical sketch of the robot's core rotary joint transmission mechanism; (D) Structural rendering of the personalized limb-fixing end effector; (E) 3D workspace reachability simulation result of the robot operating end; (F) Application render showing a seated patient using the robot for upper limb rehabilitation training.

adaptation calibration, the terminal repeat positioning accuracy of 0.1 mm is achieved on the premise of ensuring performance, and the weight of the whole machine is much lower than the traditional 50 kg rehabilitation equipment, which is convenient for deployment in multiple scenarios.

3. Multi-Modal Sensing and Adaptive Control Strategy

3.1. Overall Framework of the Closed-Loop Control System

The control system adopts a closed-loop data flow architecture of "end sensor acquisition → data preprocessing → main control unit operation → power execution → attitude feedback calibration". The end 3D force sensor, surface electromyography electrode, and inertial measurement unit synchronously collect multi-source data, and the control board calculates the control quantity in real time and drives the actuator to move, forming a complete closed-loop control.

3.2. Multi-Modal Data Fusion and Signal Denoising

Aiming at the problems of nonlinear characteristics, multi-source heterogeneity, and noise interference of multi-modal sensor data, a data fusion method combining an extended Kalman filter (EKF) and a convolutional neural network (CNN) is proposed. The EKF algorithm performs optimal state estimation on multi-source dynamic signals through a closed prediction-update iteration cycle, effectively suppressing random noise in sEMG, 3D force, and kinematic signals, and outputs smoothed state quantities with minimum variance [10]. The principle of the EKF-based state estimation and data fusion framework is illustrated in **Figure 2(A)**. On this basis, a CNN-based deep feature extraction module is constructed to mine

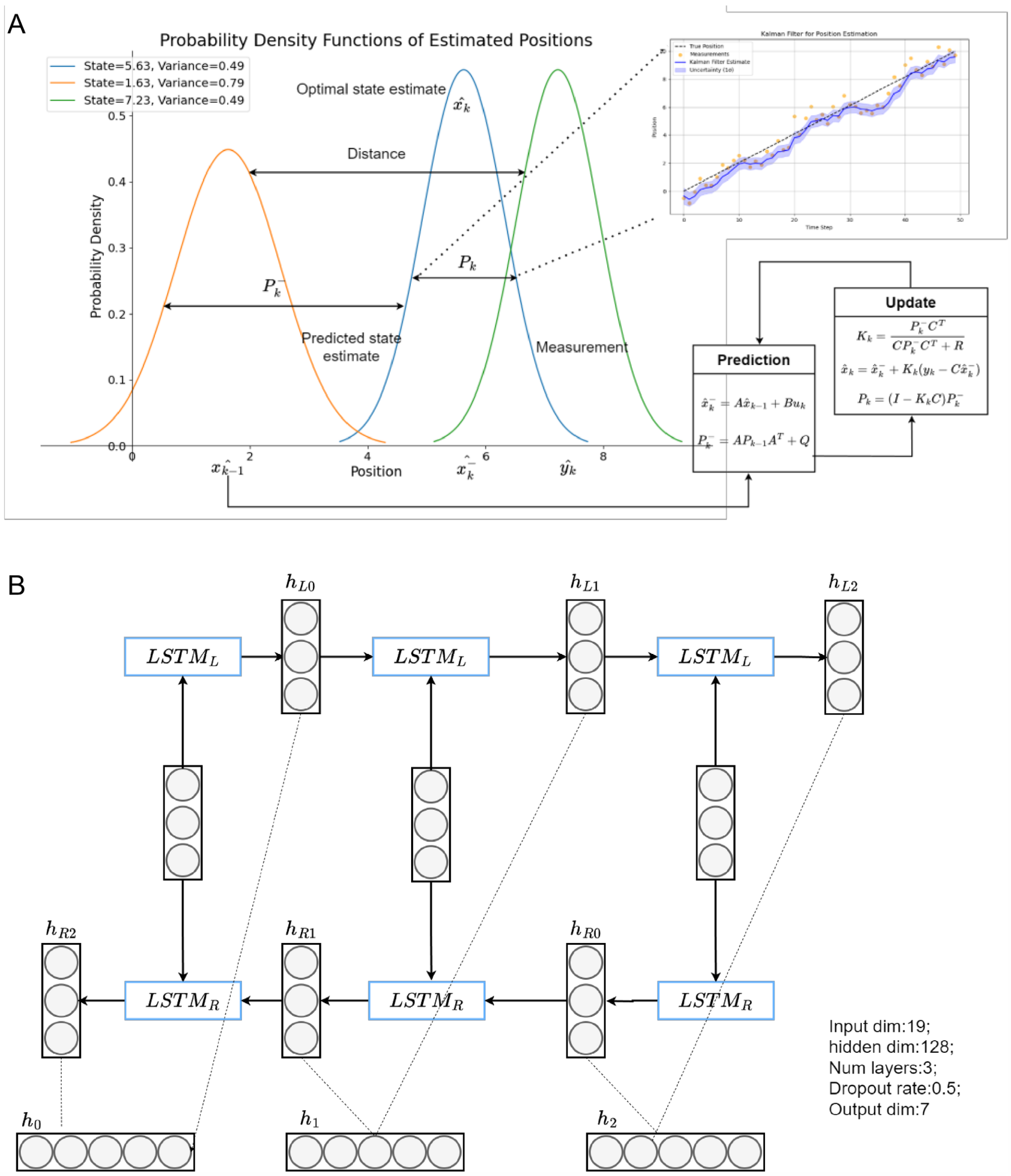

Figure 2. Architecture of the multi-modal sensing fusion and adaptive trajectory prediction algorithm. (A) Schematic of the Kalman filter-based multi-modal sensor data fusion and state estimation framework, which denoises raw signals and generates optimal state estimation through the prediction-update cycle; (B) Structure of the proposed bidirectional LSTM model with attention mechanism for end-effector motion trajectory prediction, designed for nonlinear and high-dynamic rehabilitation scenarios.

the latent nonlinear features of different modal data, and a nonlinear fusion strategy is adopted to realize the deep interaction of cross-modal features, which provides high signal-to-noise ratio data input for subsequent motion intention recognition and trajectory prediction.

3.3. Adaptive Trajectory Prediction Based on BiLSTM-Attention

To realize an accurate prediction of the robot end-effector motion trajectory in nonlinear and high-dynamic rehabilitation scenarios, a bidirectional long short-term memory (BiLSTM) network with an attention mechanism is constructed in this study. As shown in **Figure 2(B)**, the network adopts a bidirectional symmetric architecture composed of forward and reverse LSTM layers, which can capture the temporal dependence of motion sequence data from both past and future directions.

Aiming at the time-series characteristics of rehabilitation motion data, a bidirectional long short-term memory (BiLSTM) model with an attention mechanism is constructed to predict the robot's end motion trajectory over the next 300 ms. The trajectory prediction method based on multi-modal rehabilitation data has been protected by an authorized invention patent [11]. The attention mechanism is introduced to weight key motion features, which improves the prediction accuracy in nonlinear and high-dynamic scenarios, and the trajectory prediction error in complex rehabilitation scenarios, such as grasping and shaking, is less than 2 cm.

On this basis, a reinforcement learning framework is introduced to build an adaptive control strategy. The system can adjust the auxiliary torque and motion trajectory in real time according to the patient's posture change, external force interference, and sudden spasm, so as to avoid secondary injury caused by "one-size-fits-all" training.

3.4. Impedance Control Model for Rehabilitation Training

An impedance control model based on force-position hybrid control is established, and the stiffness coefficient K of the robot is adjusted according to the patient's muscle strength level:

$$F_{assist} = K\left(\theta_{target} - \theta_{actual}\right) + B\dot{\theta} \tag{1}$$

where F_{assist} is the equivalent auxiliary force at the end effector, θ_{target} and θ_{actual} are the target joint angle and actual joint angle, respectively, $\dot{\theta}$ denotes the angular velocity of the joint, and B is the damping coefficient. The stiffness coefficient K is adaptively adjusted in real time based on the patient's sEMG-derived muscle strength level: it is set to a large value in the early rehabilitation stage to provide sufficient trajectory guidance and support force, and decreases gradually as motor function recovers [12]. This adaptive power assistance control strategy has been granted an invention patent [13].

4. Immersive AR Interactive Training System

4.1. System Architecture of AR Training Module

Aiming at the problem of boring training process and low patient compliance of traditional rehabilitation robots [14], an immersive AR interactive training system is built based on 3D engine technology. The system constructs a task-oriented, game-based rehabilitation framework that covers passive, assistive, and resistive training modes and designs targeted virtual scenarios for different rehabilitation stages, from early limb motion induction to late muscle strength improvement.

The system supports multi-terminal adaptation, including desktop computers, tablets, and AR head-mounted displays. Through motion synchronous rendering and a haptic-visual linkage mechanism, it realizes real-time mapping between the robot end-effector motion and virtual scene interactions, providing patients with an immersive integrated rehabilitation experience. Representative AR training scenarios of the system are shown in **Figure 3**.

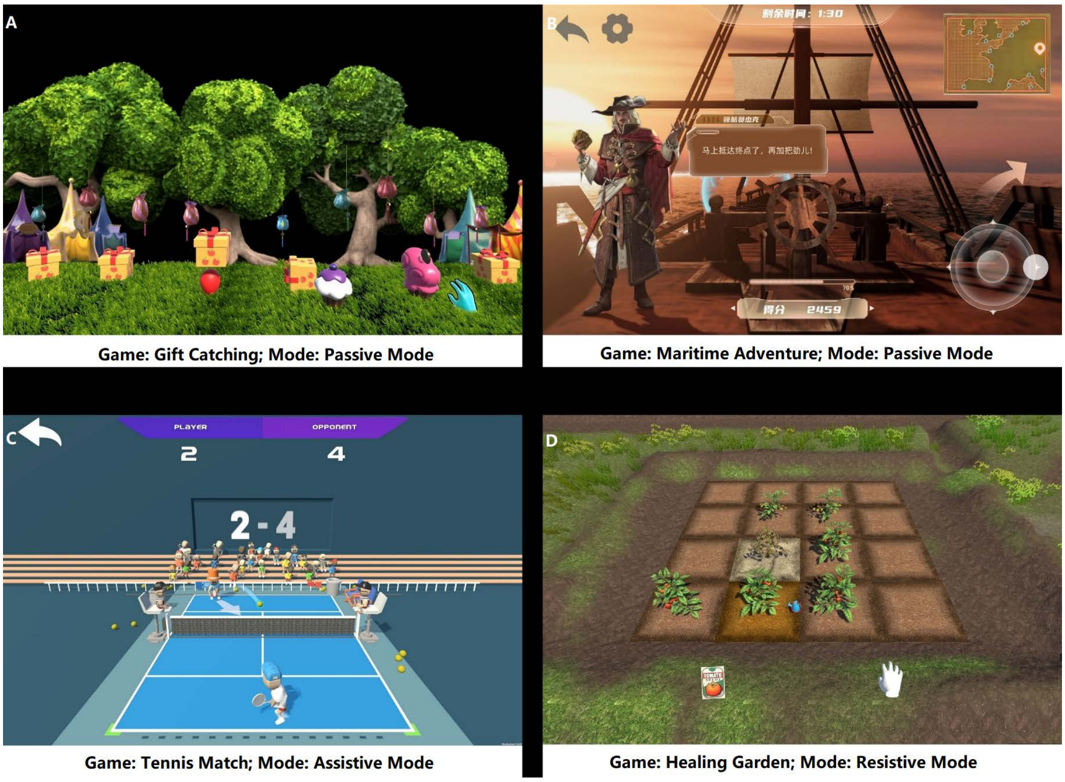

Figure 3. Representative AR game-based training scenarios of the developed upper limb rehabilitation robot. (A) Gift Catching task in passive training mode, applied for guided limb motion induction in early-stage rehabilitation; (B) Maritime Adventure task in passive training mode, embedded with real-time motivational feedback to enhance patient engagement; (C) Tennis Match task in assistive training mode, designed to improve upper limb coordination with supplementary power assistance during active movement; (D) Healing Garden task in resistive training mode, for muscle strength enhancement and fine motor function training in middle-late rehabilitation stages.

4.2. Dynamic Scene Generation and Adaptive Difficulty Adjustment

A multi-person collaborative scene editing system is developed, which allows doctors and therapists to design or modify AR training tasks collaboratively through the cloud, and customize trajectory constraints, resistance parameters, and task objectives. The system is pre-installed with more than 10 types of standardized virtual training scenarios covering upper limb fine function training, such as transfer, guidance, positioning, and grasping.

The system can automatically switch the scene complexity according to the patient's Brunnstrom stage: low-difficulty tasks are adopted for early passive training, and multi-joint coordination challenges are upgraded for later active training, so as to realize the precise matching of rehabilitation schemes in different stages.

4.3. Lightweight Asynchronous Feedback Architecture

A single-threaded asynchronous rendering architecture is adopted to realize parallel processing of multi-sensor data on low-computing terminals such as tablets and AR glasses, which reduces memory occupation by 70% and controls the interaction feedback delay within 50 ms. The lightweight asynchronous rendering method for rehabilitation scenarios involved in this system has been authorized as an invention patent [15].

A haptic-visual synchronization mechanism is established: combined with sEMG signals and end force control data [16], when the patient's force is insufficient, the virtual object in the AR scene gives a visual color warning synchronously, and the robot automatically increases the auxiliary torque at the same time, so as to realize the synchronous feedback of visual perception and force perception.

5. Experimental Validation and Performance Analysis

5.1. Test Setup

5.1.1. Bench Test Protocol

To verify the performance of the developed rehabilitation robot, systematic bench tests were carried out. All bench tests were conducted in a standard temperature and humidity laboratory environment (23˚C, 50% RH), and performed in strict accordance with the YY 9706 (aligned with IEC 60601) series standards for medical electrical equipment [17]. The test scheme covers four dimensions: hardware performance, control performance, interactive performance, and safety performance, with core indicators including terminal repeat positioning accuracy, trajectory tracking error, system response delay, AR interaction latency, operating noise, and overload protection threshold. Key performance indicators were independently verified by a CMA-accredited third-party medical device testing institution to ensure the objectivity and credibility of the test data.

5.1.2. Clinical Pilot Trial Protocol

The preliminary clinical pilot trial was reviewed and approved by the Ethics Committee of Hangzhou First People's Hospital (Approval No. [2024] 562). The study was strictly implemented in accordance with the Declaration of Helsinki, and all enrolled subjects signed written informed consent prior to participation.

Inclusion criteria were defined as: first-onset stroke confirmed by cranial CT/MRI, age 40 - 75 years, Brunnstrom stage II - V of the affected upper limb, stable vital signs, and ability to cooperate with rehabilitation training. Exclusion criteria included severe cognitive impairment, severe limb spasm (Modified Ashworth Scale ≥ grade 4), combined upper limb joint deformity, and other serious systemic diseases.

A self-controlled study design was adopted. A total of 20 eligible post-stroke patients with upper limb motor dysfunction were recruited, with baseline Brunnstrom stages covering II to V. All subjects had received conventional manual rehabilitation for 2 weeks before enrollment, and their baseline motor function and training efficiency data were collected as the control period. After enrollment, all patients received 4 weeks of robot-assisted rehabilitation training (30 min per session, 5 sessions per week) on the basis of conventional rehabilitation therapy. The primary evaluation indicators included the Fugl-Meyer Assessment for Upper Extremity (FMA-UE) score, modified Barthel Index (MBI), active motion induction rate, daily effective training duration, and incidence of adverse events [18].

5.2. Core Performance Bench Test Results

5.2.1. Hardware Performance

Bench test results show that the terminal repeat positioning accuracy of the robot reaches 0.08 mm ± 0.02 mm, and the steady-state trajectory tracking error is controlled at 0.1 mm, which is significantly better than the ±0.5 mm accuracy level of mainstream imported rehabilitation equipment [19]. Benefiting from the topology optimization of the hybrid parallel-serial mechanism and the full localization of core components such as servo motors and precision reducers, the localization rate of core functional components of the whole machine reaches 100%, and the overall weight is reduced by more than 40% compared with traditional 50 kg-grade rehabilitation equipment, which is convenient for multi-scenario deployment.

5.2.2. Control Performance

The closed-loop control system achieves a dynamic response delay of 22 ms ± 4 ms, which is far better than the industry average level of >100 ms, and fully meets the real-time control requirements of rehabilitation training. The system supports four training modes: passive, assistive, active, and resistive, with a weight assistance accuracy error ≤ 0.15 kg, which can cover the rehabilitation needs of patients at different Brunnstrom stages [20] and realize smooth switching between modes.

5.2.3. Interactive Performance

Benefiting from the proposed lightweight asynchronous rendering architecture, the end-to-end delay of AR interactive feedback is controlled at 42 ms ± 6 ms, which is significantly lower than the >200 ms latency level of similar AR rehabilitation systems. The system is equipped with more than 10 built-in standardized virtual training scenarios covering upper limb fine motor functions such as transfer, positioning, and grasping, and supports multi-terminal adaptation of tablets and AR head-mounted devices.

The detailed comparison of core performance indicators between the proposed system and the industry average level is summarized in **Table 1**. The results show that the core indicators of the system reach the international advanced level, and have obvious advantages in localization degree, control response speed, and interactive performance.

Table 1. Comparison of core performance indicators between the proposed robot and the industry average.

Index Category	Specific Parameters of This System	Industry Average Level
Hardware performance	100% localization rate of core components; 0.1 mm terminal repeat positioning accuracy; 0.1 mm motion trajectory accuracy	60% localization rate for domestic devices; ±0.5 mm terminal accuracy for imported devices
Control performance	System response delay ≤ 30 ms; supports 4 training modes (passive/assistive/active/resistive); weight assistance accuracy error ≤ 0.2 kg	Response delay > 100 ms; most devices only support 2 - 3 training modes
Interaction performance	AR interaction delay ≤ 50 ms; built-in 10+ virtual training scenarios; supports multi-terminal adaptation	Most devices have no AR interaction, or a delay > 200 ms, with few scenarios
Safety performance	Equipment noise ≤ 55 dB(A); integrated multi-safety protection (anti-pinch, emergency stop, overload)	Meets general medical electrical standards, with lower safety redundancy

5.3. Reliability and Safety Verification

The prototype completed a 100,000-cycle reciprocating motion fatigue test under full-load operating conditions, with no mechanical failure, component wear, or control accuracy degradation observed during the test. The estimated mean time between failures (MTBF) is greater than 10,000 hours, which supports 7 × 24 hours of long-term continuous operation and meets the high-frequency use requirements of clinical rehabilitation scenarios.

In terms of electrical safety and electromagnetic compatibility, the product has passed a full-item inspection by a CMA-accredited third-party testing institution and fully complies with the YY 9706.1 series standards for electric shock protection, mechanical safety, electromagnetic compatibility, and environmental adaptability. The device integrates multiple graded safety protection mechanisms, including anti-pinch detection, a physical emergency stop button, and overload current limiting, which can trigger protection actions within 10 ms in abnormal conditions such as excessive traction force or sudden limb spasm, effectively preventing secondary injury to patients.

5.4. Preliminary Clinical Pilot Trial Results

5.4.1. Upper Limb Motor Function Outcomes

After 4 weeks of robot-assisted rehabilitation intervention, the Fugl-Meyer Assessment for Upper Extremity (FMA-UE) score of the enrolled patients increased from 28.4 points ± 6.3 points at baseline to 39.7 points ± 7.1 points, with a mean improvement rate of 39.8% ($P < 0.01$, paired t-test). The modified Barthel Index

(MBI) increased from 52.5 points ± 8.6 points to 68.3 points ± 9.4 points ($P <$ 0.05), indicating a significant improvement in patients' activities of daily living.

Among the 20 subjects, 14 patients achieved at least one-stage improvement in the Brunnstrom stage, with an improvement rate of 70%. Compared with the functional progression rate observed during the pre-enrollment conventional manual rehabilitation phase, the average Brunnstrom stage progression cycle was shortened by approximately 40% under robot-assisted training.

5.4.2. Training Efficiency and Compliance

Quantitative statistics show that under robot-assisted training, the active motion induction rate of patients reaches 72%, and the average daily effective training duration reaches 45 min. Both indicators are notably higher than the 42% induction rate and 25 min effective duration widely reported in conventional manual rehabilitation literature [21]. The incidence of ineffective training is controlled at 10%, which is significantly lower than the general level of 30% in traditional training modes.

5.4.3. Safety Profile

During the entire pilot trial, no adverse events such as muscle strain, joint pain, skin pressure injury, or secondary motor injury occurred in all subjects. The equipment operated stably throughout the trial period, with no safety failures such as out-of-control motion, abnormal force output, or system crash, which preliminarily verified the clinical safety and operational stability of the system.

6. Discussion

This study proposes an AR-enhanced upper limb rehabilitation robot with adaptive trajectory control, which has made breakthroughs in mechanism design, intelligent control, and interactive experience. Compared with existing research, the innovation of this system is mainly reflected in three aspects:

1) The hybrid parallel-serial mechanism takes into account both working space and control accuracy, and realizes full localization of core components, which significantly reduces the cost of the whole machine and improves the accessibility of primary medical scenarios.

2) The multi-modal fusion adaptive control strategy realizes real-time perception and dynamic adjustment of the patient's motor state, which solves the problem of poor adaptability of traditional fixed trajectory training.

3) The lightweight asynchronous AR interaction system realizes haptic-visual synchronous feedback, which effectively improves patient compliance and neural plasticity activation efficiency.

This study still has some limitations. First, the sample sizes of preliminary clinical trials are small, and large-sample randomized controlled trials are needed to further verify clinical efficacy. Second, the current evaluation system focuses on motor function, and the evaluation of cognitive function and psychological state needs further enrichment. In future work, we will continue to promote clinical trials, optimize the multi-modal rehabilitation evaluation model, and explore the integration of brain-computer interface technology to further improve the intelligence level of the system.

7. Conclusions

This paper presents the design, implementation, and experimental validation of an AR-enhanced upper limb rehabilitation robot with adaptive trajectory control. The system adopts a hybrid parallel-serial mechanical structure, builds a multimodal sensing adaptive control system, and develops an immersive AR interactive training module, effectively addressing the pain points of traditional rehabilitation robots, such as low accuracy, poor adaptability, and low compliance. Bench tests and preliminary clinical verification prove that the system has advanced core performance and good rehabilitation effect, and has broad application prospects in clinical rehabilitation, community rehabilitation, and home rehabilitation.

In the next step, we will carry out large-scale multicenter clinical trials to further verify the clinical efficacy and safety of the system; promote the registration of Class II medical devices to accelerate the industrial transformation of the achievements; and continue to iterate the intelligent algorithm to build a more complete closed-loop rehabilitation system of "evaluation-training-feedback-optimization".

Author Contributions

Weiwei Wen: Writing—original draft; formal analysis (clinical data statistics and analysis). Hanyang Xu: Methodology; development and implementation of the adaptive trajectory control system. Fanghui Qiu: Validation; design of the clinical validation protocol. Tianxiao Chen: Investigation; clinical data collection and curation. Yu Wang: Conceptualization; funding acquisition; Writing—review & editing; overall study supervision.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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