

Article

Adaptive Motion Intention Estimation and Impedance Learning for Human–Robot Interaction

Xinglong Pei, Liqun Wen , Xiaoke Fang and Jianhui Wang *

College of Information Science and Engineering, Northeastern University, Shenyang 110819, China; 1810270@stu.neu.edu.cn (X.P.); 2310336@stu.neu.edu.cn (L.W.); fangxiaoke@mail.neu.edu.cn (X.F.)

* Correspondence: wangjianhui@mail.neu.edu.cn

Abstract

This paper proposes a safe and effective human–robot physical interaction control framework for exoskeleton robots that enhances system compliance and safety while enabling the robot to adapt to human motion. The framework is designed around two primary objectives: first, a model-free adaptive control method is employed for reference trajectory estimation to achieve real-time estimation of human motion intention; second, the Forgetting Factor Recursive Least Squares (FFRLS) method is utilized for online estimation and the learning of human impedance parameters, considering their time-varying nature. In addition, a model-free adaptive trajectory tracking control strategy is proposed to optimize control performance during human–robot physical interaction. Simulation results demonstrate that the proposed control framework outperforms conventional methods significantly in terms of safety and compliance.

Keywords: robotic rehabilitation; motion intention estimation; impedance learning; model-free adaptive control (MFAC); forgetting factor recursive least squares (FFRLS)

1. Introduction

When stroke patients with hemiplegia enter Brunnstrom Stage III and beyond in the active training phase, how rehabilitation robots detect patient movement intention during human–robot physical interaction remains a challenge. If the robot fails to recognize patient intention, it may become an additional load; conversely, if intention is accurately perceived, patients can easily guide the robot's motion, not only significantly reducing physical effort but also enhancing active participation and promoting neurological functional reorganization [1]. Therefore, motion intention estimation has become one of the core issues in rehabilitation robot research [2]. Notably, due to muscle weakness and abnormal movement patterns, stroke patients exhibit dynamically varying human impedance characteristics that differ significantly from healthy individuals; fixed impedance control can easily lead to unnatural interaction or patient fatigue [3,4]. Thus, how to enable robots to adaptively adjust desired impedance based on patient impedance is also crucial to achieving natural human–robot collaboration.

Accurate estimation of patient movement intention is essential to compliant human–robot interaction. Traditional methods rely on explicit dynamic models, deriving intentions through model-based compensation and residual force extraction and then converting residual forces into intended trajectories via impedance relationships [5,6]. These methods require precise identification of multiple dynamic parameters; however, modeling errors or parameters drift directly degrade estimation results, leading to compensation failure.



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Moreover, rehabilitation robot systems face complex conditions, including human–robot coupling, time-varying loads, and nonlinear friction, rendering precise modeling not only costly but also inadequate for ensuring real-time adaptability. To address this, we adopt the model-free adaptive control (MFAC) framework to directly learn dynamic relationships in human–robot interaction from input–output data [7,8]. This method utilizes locally linear mapping coefficients updated online to establish data-driven relationships between interaction force changes and intended trajectory changes, thereby achieving real-time intention estimation through online adaptive updates without any prior dynamic parameters and fundamentally overcoming traditional methods' reliance on precise dynamic models.

Furthermore, human impedance parameters are key indicators describing muscle stiffness and damping characteristics, directly affecting interaction compliance and safety [9]. During rehabilitation, stroke patients exhibit significant time-varying and individual differences in impedance characteristics due to neuromuscular damage, with dynamic changes throughout the recovery process. If robots employ fixed impedance parameters, they struggle to adapt to patients' continuously changing physiological states, easily causing excessive interaction forces or insufficient compliance, affecting rehabilitation outcomes or even causing secondary injury. Therefore, achieving online learning and adaptive adjustment of human impedance parameters is an important direction for enhancing rehabilitation robot intelligence. Existing impedance learning methods mainly rely on preset models or offline identification, making it difficult to meet real-time and adaptability requirements [10]. Although reinforcement learning strategies [11,12] are also commonly employed for impedance parameter learning, their core objective lies in optimizing specific performance metrics (e.g., energy consumption and stability margin) through optimal configuration of stiffness/damping parameters, focusing on online optimization and adaptive adjustment of impedance parameters rather than the real-time tracking of time-varying parameters. Consequently, when confronted with the time-varying characteristics of impedance parameters in rehabilitation environments, particularly the dynamic tracking of rhythmic muscle activation changes during rehabilitation training, reinforcement learning methods exhibit inherent limitations and are hardly directly applicable. To this end, we employ Forgetting Factor Recursive Least Squares (FFRLS) for online estimation and the learning of human impedance parameters [13,14]. FFRLS introduces a forgetting factor to exponentially weight historical data, enabling the algorithm to track parameter time-varying characteristics while utilizing recursive update mechanisms to reduce computational complexity and meet real-time requirements. Specifically, this method takes interaction force and position deviation as inputs, updating stiffness and damping parameter estimates online by minimizing prediction error, without requiring preset human dynamic models. Compared with traditional batch least squares, FFRLS offers stronger adaptive capabilities and lower computational overhead, particularly suitable for scenarios where patient impedance characteristics continuously evolve during rehabilitation. Based on online-estimated impedance parameters, robots can dynamically adjust desired admittance models, achieving personalized interaction control with both rigidity and compliance.

To ensure control performance during human–robot physical interaction, we further propose a model-free adaptive trajectory tracking control strategy. The motivation is that existing execution controllers primarily adopt PID control [15–17]. While this approach can achieve basic control objectives, it struggles to address the time-varying and uncertain interaction models between exoskeleton robots and human upper limbs. Although advanced methods such as adaptive control and sliding mode control have improved controller parameter selection and anti-interference capabilities to some extent, they still have strict requirements for modeling accuracy and environmental disturbances. To address these

challenges, data-driven methods have gradually gained attention [18,19]. Data-driven control directly uses input–output data obtained from the controlled system to design controllers, without utilizing explicit mathematical models of the controlled process, thereby avoiding complex issues such as system modeling, unmodeled dynamics, and robustness analysis. As a typical data-driven control method, MFAC has broad engineering application prospects due to its low computational requirements [20–22]. Unlike model-based methods that analyze and predict dynamic behavior of controlled objects, MFAC controller design and implementation require only input–output data. The controlled object is transformed into an equivalent data model, emphasizing the dynamic relationship between output changes and control input changes. This method utilizes online-updated local linear mapping coefficients to establish data-driven relationships between interaction force changes and trajectory tracking errors, without requiring any prior dynamic parameters, and achieves real-time adjustment of control parameters through online adaptive updates. With its minimal computational requirements and sole dependence on input–output data, MFAC provides a robust solution for controlling human–robot interaction systems with uncertainties, particularly suitable for complex systems such as exoskeleton rehabilitation robots that are difficult to model precisely.

Despite the aforementioned advances, a critical examination of the existing literature reveals significant unresolved challenges that motivate this work. Existing MFAC-based approaches primarily focus on either intention estimation or controller design in isolation, lacking a unified framework that simultaneously addresses intention perception, impedance adaptation, and stable trajectory execution. While traditional model-based methods [5,6] suffer from parameter dependency and real-time adaptability issues, current data-driven alternatives have not fully exploited the potential of integrating multiple functional modules. Although advanced model-based methods such as adaptive sliding mode control (ASMC) have improved robustness against disturbances and uncertainties to some extent, they still rely on approximate dynamic models and require prior knowledge of system bounds, making them difficult to adapt to the highly time-varying and patient-specific characteristics of rehabilitation environments. Furthermore, neural network (NN)-based uncertainty handling methods, despite their capability to compensate for unknown dynamics and external disturbances through function approximation, typically require extensive offline training data, and the black-box nature of neural networks renders it difficult to provide interpretable stability guarantees, limiting their applicability in safety-critical rehabilitation scenarios. Three interconnected gaps persist: (i) no existing methods achieve synchronous online estimation of both human impedance and movement intention within a single data-driven framework; (ii) reinforcement learning-based impedance optimization [11,12] focuses on parameter configuration for performance metrics rather than the real-time tracking of time-varying impedance parameters, which is essential to capturing the rhythmic muscle activation changes characteristic of stroke rehabilitation; (iii) execution controllers under model-free adaptive frameworks lack rigorous closed-loop stability guarantees, particularly when simultaneously handling time-varying impedance adaptation and intention-driven trajectory modification, whereas ASMC-based methods, despite their stability proofs, are constrained by model dependency and cannot be directly applied to the data-driven setting considered herein, and NN-based methods, while capable of handling uncertainties, fundamentally fail to resolve the contradiction between model dependency and provable stability. These limitations are especially critical in stroke patients in Brunnstrom Stage III and beyond, where muscle weakness and abnormal movement patterns create dynamically varying impedance profiles that conventional fixed or offline-identified parameters cannot adequately accommodate. This paper addresses the following core question: how a rehabilitation robot can simultaneously estimate patient

movement intention, learn time-varying human impedance parameters, and achieve provably stable trajectory tracking in a unified data-driven framework without relying on explicit dynamic models.

Based on the above discussion, this paper proposes a combined method integrating movement intention estimation and impedance learning. Specifically, while achieving the robot learning of patient movement intentions, we introduce identification of human impedance characteristics and propose a model-free adaptive control strategy.

The main innovations of this paper are as follows:

- (1) Overcoming the limitation of traditional methods that focus only on single parameters, we established a synchronous online estimation framework for both human impedance and movement intention, enabling robots to dynamically adjust assistance strategies according to patient active participation levels, achieving active rehabilitation training cooperation.
- (2) Addressing dynamic uncertainties in rehabilitation robots, we propose a data-driven model-free adaptive control method that achieves controller parameter self-tuning through online data mining, jointly designing the execution controller with stability analysis to ensure closed-loop system stability.
- (3) Designing data-driven model-free adaptive trajectory tracking control to achieve precise regulation of robot operating space, ensuring training safety from both velocity and position dimensions, forming an intelligent rehabilitation control system with synergistic integration of high-precision tracking, adaptive impedance, and safe operation.

This article is organized as follows: In Section 2, preliminaries for active rehabilitation training are presented. The overall framework design is presented in Section 3, including motion intention estimation, impedance learning, and position controller design. Simulation and results are given in Section 4.

Notation: Δ denotes the difference operator defined by $\Delta z(\kappa) = z(\kappa) - z(\kappa - 1)$, and κ denotes an instant moment. $\|\cdot\|$ represents the Euclidean vector norm.

2. Preliminaries

2.1. System Dynamics

In joint space, the dynamics of robotic exoskeleton are represented as follows:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + F(\dot{q}) + G(q) + \delta = \tau_c + \tau_h, \quad (1)$$

where $q \in \mathbb{R}^{n \times 1}$ is the vector of joint variables and n denotes the degrees of freedom (DOF); $M(q) \in \mathbb{R}^{n \times n}$ is the inertia matrix; $C(q, \dot{q}) \in \mathbb{R}^{n \times n}$ denotes the Coriolis and centrifugal forces; $F(\dot{q}) \in \mathbb{R}^{n \times 1}$ is the friction term; $G(q) \in \mathbb{R}^{n \times 1}$ is the gravity term; $\delta \in \mathbb{R}^{n \times 1}$ denotes unknown disturbances from the external environment; $\tau_c \in \mathbb{R}^{n \times 1}$ is the control torque; and the human–robot interaction torque is $\tau_h = J^T f_h$, with $J \in \mathbb{R}^{n \times n}$ being the Jacobian matrix [23] and $f_h \in \mathbb{R}^{n \times 1}$ the human–robot interaction force.

Property 1 [24]. $M(q)$ is a symmetric and positive definite inertia matrix.

Property 2 [24]. $\dot{M}(q) - 2C(q, \dot{q})$ is a skew-symmetric matrix, if $C(q, \dot{q})$ is in the Christoffel form, i.e., $\zeta^T (\dot{M}(q) - 2C(q, \dot{q})) \zeta = 0, \forall \zeta \in \mathbb{R}^{n \times 1}$.

The forward kinematics of the robotic exoskeleton is defined as:

$$X = \phi(q), \quad (2)$$

where $\phi(\cdot)$ is the function of the forward kinematics and $X \in \mathbb{R}^{n \times 1}$ is the position of the robot end-effector in Cartesian space. By differentiating both sides of Equation (2), one gets

$$\dot{q} = J^+ \dot{X}, \quad (3)$$

where $\dot{X} \in \mathbb{R}^{n \times 1}$ is the velocity of the robot end-effector and J^+ denotes the pseudoinverse of J and can be given by $J = J^T (JJ^T)^{-1}$.

Given that the inverse kinematics may lead to issues such as drift and computational burden, the Closed-Loop Inverse Kinematics (CLIK) method [25] is adopted. By employing the CLIK method, the Equation (3) can be reformulated as:

$$\dot{q} = k_q J^T e, \quad (4)$$

where k_q is the control gain and e is the error.

The dynamics of the human upper limb are considered as [26,27]

$$f_h = -B_h \dot{X} + K_h (X_d - X), \quad (5)$$

where B_h and K_h are the damping and stiffness matrices of the human limb, respectively, and both are diagonal matrices; X is the robot motion trajectory; and X_d is the trajectory planned by the human central nervous system, referred to as the human motion intention in this paper, which is constrained to be the trajectory closest to the end-effector.

2.2. Admittance Control

Impedance control [28–30] provides an established mechanism to specify a dynamic relationship between position and force in a system and provide controllable DOFs with definable degrees of compliance [31,32]. This is well suited to human–robot interaction (HRI) and has been widely applied in rehabilitation robotics to vary the assistance provided by the robot. According to the cause-and-effect relationship, position-based impedance control is called admittance control [33]. In [28,29], it is pointed out that admittance control can define any dynamic relationship between position and force, and a spring–damper arrangement is appropriate to HRI systems. Thus, the desired robot admittance model is defined as:

$$f_h = -B_d \dot{X}_r + K_d (\hat{X}_d - X_r), \quad (6)$$

where B_d and K_d denote the desired damping matrix and stiffness matrix, respectively. X_r is the modified desired trajectory. By using the inverse kinematics as $q = \phi^{-1}(X)$; the corresponding trajectory in joint space is generated as $q_r = \phi^{-1}(X_r)$ with the interaction torque τ_h . An adaptive model-free control (MFAC) method is designed for unmodeled dynamics and unknown disturbances to ensure trajectory tracking: $\lim_{\kappa \rightarrow +\infty} q(\kappa) \rightarrow q_r(\kappa)$. If the ideal tracking performance is achieved, there exists $q(\kappa) = q_r(\kappa)$, and $X(\kappa) = X_r(\kappa)$. Thus, the Equation (6) is written as:

$$f_h = -B_d \dot{X} + K_d (\hat{X}_d - X). \quad (7)$$

The overall block diagram is shown in Figure 1, which illustrates the architecture of the proposed adaptive admittance control system for upper-limb rehabilitation. The system consists of five interconnected functional modules: (1) Motion Intention Estimator: It estimates human upper-limb motion intention and generates the reference velocity $\hat{X}_d$, providing target motion guidance for rehabilitation training. (2) Human Impedance Learning Module: It employs the Forgetting Factor Recursive Least Squares (FFRLS) algorithm to estimate online the time-varying human endpoint impedance parameters,

including stiffness K_h and damping B_h , enabling adaptation to the patient's changing neuromuscular condition during rehabilitation. (3) Admittance-Based Trajectory Modifier: It establishes a human–robot interaction dynamic model based on the estimated admittance parameters and measured interaction force f_h , computing the modified reference position X_r that complies with the patient's physical capability. (4) Position Tracking Controller: It generates control torque commands according to the tracking error between the modified reference position X_r and the actual robot position X , ensuring precise trajectory following. (5) Rehabilitation Robot Platform: A 5-degree-of-freedom flexible joint manipulator that physically interacts with the patient's upper limb, delivering the required assistive torque for task-oriented rehabilitation training. In addition, the system includes a force signal acquisition module and an environmental factor module.

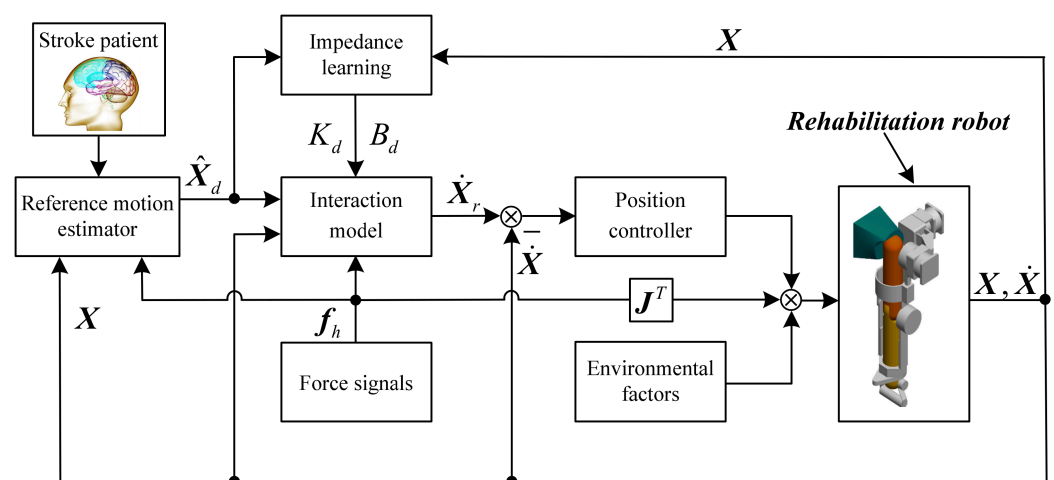


Figure 1. Control framework.

3. Framework Design

3.1. Design of Motion Intention Estimation and Impedance Learning

In this section, a model-free adaptive control (MFAC) method is proposed for online estimation of patient motion intention, aiming to overcome the reliance of traditional methods on precise dynamic models. Based on this intention estimation, the impedance adaptation strategy is as follows: when the patient acts as the leader during interaction, the robot reduces stiffness to enhance compliance, facilitating patient operation; when the patient is in following mode, the robot should increase the desired stiffness to ensure tracking accuracy of the reference trajectory.

When the system reaches a steady state or quasi-steady state, the human body model in Equation (5) can be described as:

$$X_d(\kappa) = X(\kappa) + K_h^{-1} f_h(\kappa). \quad (8)$$

Since the model parameter K_h is unknown, X_d cannot be directly calculated from Equation (8). This paper adopts the MFAC data-driven approach to directly estimate K_h^{-1} , thereby achieving online estimation of $\hat{X}_d$.

Remark 1. The core idea of the MFAC method for motion intention estimation is to treat K_h^{-1} as a time-varying parameter to be estimated and use the dynamic linearization technique to establish the dynamic relationship between ΔX and Δf_h , avoiding explicit dependence on the unknown parameter K_h .

According to the dynamic linearization technique [34], taking the difference of Equation (8) at adjacent time instants eliminates the influence of the unknown constant X_d , yielding the difference form

$$\Delta X(\kappa) = -K_h^{-1} \Delta f_h(\kappa), \quad (9)$$

where $\Delta X(\kappa) = X(\kappa) - X(\kappa - 1)$ and $\Delta f_h(\kappa) = f_h(\kappa) - f_h(\kappa - 1)$.

We transform Equation (9) into the Compact Form Dynamic Linearization (CFDL) discrete data model:

$$\Delta X(\kappa) = \Phi(\kappa - 1) \Delta f_h(\kappa), \quad (10)$$

where $\Phi(\kappa) \in \mathbb{R}^{n \times n}$ is the Pseudo-Partial Derivative (PPD) matrix, representing the time-varying estimation of the inverse of human limb stiffness matrix $-K_h^{-1}$, satisfying $\Phi(\kappa) \rightarrow -K_h^{-1}$ at steady state.

Remark 2. It should be noted that $\Delta f_h(\kappa) = f_h(\kappa) - f_h(\kappa - 1)$ characterizes the interaction force variation at the current time instant, while $\Psi(\kappa - 1)$ represents the most recently available Pseudo-Partial Derivative (PPD) estimation matrix. This data model achieves real-time parameter updating by making full use of the latest measurement information, conforming to the standard implementation paradigm of the model-free adaptive control (MFAC) framework.

Consider the following criterion function for estimating $\Phi(\kappa)$:

$$J(\Psi(\kappa)) = \|\Delta X(\kappa) - \Phi(\kappa) \Delta f_h(\kappa)\|^2 + \zeta \|\Phi(\kappa) - \Phi(\kappa - 1)\|^2, \quad (11)$$

where $\zeta > 0$ denotes the weighting factor.

Minimizing Equation (11) yields:

$$\Phi(\kappa) = \Phi(\kappa - 1) + \frac{\vartheta [\Delta X(\kappa) - \Phi(\kappa - 1) \Delta f_h(\kappa)] \Delta f_h^T(\kappa)}{\|\Delta f_h(\kappa)\|^2 + \zeta}, \quad (12)$$

where $\vartheta \in (0, 2]$ denotes the step-size factor.

Remark 3. Equation (12) achieves data-driven estimation of the unknown parameter K_h^{-1} by using only measurable position variation $\Delta X(\kappa)$ and force variation $\Delta f_h(\kappa)$, avoiding the difficulty of unknown K_h in model (8).

Based on the estimated $\Phi(\kappa)$, the online estimation of human motion intention is constructed from Equation (8). Substituting $K_h^{-1} = -\Phi(\kappa)$ into Equation (8) yields

$$\hat{X}_d(\kappa) = X(\kappa) - \Phi(\kappa) f_h(\kappa). \quad (13)$$

Finally, a reset mechanism is introduced into the MFAC patient intention estimation algorithm. The algorithm flow is shown in Algorithm 1.

Next, we proceed with the design of impedance learning. As mentioned earlier, if the estimated human dynamic model parameters $\hat{B}_h$ and $\hat{K}_h$ have been obtained, the desired robot impedance can be adjusted online based on the impedance adjustment law. To this end, a human impedance learning method needs to be developed first to obtain $\hat{B}_h$ and $\hat{K}_h$.

Algorithm 1. MFAC-based patient motion intention estimation algorithm.

Initialization: Set $\Phi(0), \zeta, \vartheta, \epsilon_0 > 0$; obtain initial states $\Delta X(0), \Delta f_h(0)$; let $\kappa = 1$;
Main Loop: For $\kappa = 1, 2, \dots$, execute the following steps:
Step 1: Data acquisition: Collect current position $X(\kappa)$ and force $f_h(\kappa)$;
Step 2: Compute variations: $X(\kappa) = X(\kappa) - X(\kappa - 1)$ and $\Delta f_h(\kappa) = f_h(\kappa) - f_h(\kappa - 1)$;
Step 3: Reset condition judgment: If $\|\Delta f_h(\kappa)\| \leq \epsilon_0$ or $\|\Delta X(\kappa)\| \leq \epsilon_0$, then $\Phi(\kappa) = \Phi(\kappa - 1)$, otherwise proceed to Step 4;
Step 4: Parameter update: $\Phi(\kappa) = \Phi(\kappa - 1) + \frac{\vartheta[\Delta X(\kappa) - \Phi(\kappa - 1)\Delta f_h(\kappa)]\Delta f_h^T(\kappa)}{\|\Delta f_h(\kappa)\|^2 + \zeta}$;
Step 5: Intention estimation: $\hat{X}_d(\kappa) = X(\kappa) - \Phi(\kappa)f_h(\kappa)$;
Step 6: Continue to next loop.

If $\hat{B}_h, \hat{K}_h$ and the desired trajectory estimate $\hat{X}_d$ have been obtained, the estimated interaction force $\hat{f}_h$ can be expressed as:

$$\hat{f}_h = -\hat{B}_h \dot{X} + \hat{K}_h z, \quad (14)$$

where $z = X_d - X$ is the trajectory tracking error, and $\hat{X}_d$ is obtained from the intention estimation algorithm (as shown in Algorithm 1); X and $\dot{X}$ are actually measured by the rehabilitation robot system, and the actual interaction force f_h can also be obtained through force sensors.

Remark 4. In Equation (14), $-\hat{B}_h \dot{X}$ represents the damping force opposite to the velocity direction, and $\hat{K}_h z$ represents the stiffness force based on position error. In Algorithm 1, ϵ_0 is set to 0.001 based on the sensor resolution and signal-to-noise ratio of the force/position measurement system. This threshold effectively distinguishes between meaningful human motion intention and measurement noise or involuntary physiological tremors.

Considering the time-varying characteristics of human impedance parameters, the Forgetting Factor Recursive Least Squares (FFRLS) method is adopted for online estimation. First, define the regression vector and the parameter vector to be estimated:

$$\chi(t) = \begin{bmatrix} -\dot{X}(t) \\ z(t) \end{bmatrix}, \hat{\theta}(t) = \begin{bmatrix} \hat{B}_h(t) \\ \hat{K}_h(t) \end{bmatrix}. \quad (15)$$

Then Equation (15) can be written in the standard linear regression form:

$$\hat{f}_h(t) = \chi^T(t)\hat{\theta}(t). \quad (16)$$

Define the forgetting factor $\lambda_0 \in (0, 1]$; the parameter estimation recursive formulas are as follows:

$$\begin{cases} K(t) = \frac{P(t-1)\chi(t)}{\lambda_0 + \chi^T(t)P(t-1)\chi(t)} \\ \hat{\theta}(t) = \hat{\theta}(t-1) + K(t)[f_h(t) - \chi^T(t)\hat{\theta}(t-1)] \\ P(t) = \frac{1}{\lambda_0}[I - K(t)\chi^T(t)]P(t-1) \end{cases}, \quad (17)$$

where $\hat{\theta}(t)$ is the parameter vector to be estimated, $\chi(t)$ is the regression vector, $P(0) = \delta_0 I$ is the covariance matrix, and the initial value is usually taken as $P(0) = \delta_0 I$, where $\delta_0 = 10^3 \sim 10^6$.

The forgetting factor λ_0 determines the algorithm's memory of historical data. The selection principle is that the smaller λ_0 is, the more sensitive to new data it is, and the stronger the time-varying tracking ability is, but the estimation variance increases; the closer

λ_0 is to 1, the smoother the estimation is, but the tracking speed decreases. To cope with the time-varying characteristics of human impedance, this paper selects $\lambda_0 = 0.98 \sim 0.995$.

Based on the estimated human impedance parameters, the robot desired admittance adjustment law is designed:

$$\begin{cases} B_d(t) = \bar{B} - \hat{B}_h(t) \\ K_d(t) = \bar{K} - \hat{K}_h(t) \end{cases}, \quad (18)$$

where $\bar{B}$ and $\bar{K} \in \mathbb{R}^{n \times n}$ are the set positive definite target admittance matrices; $\hat{B}_h$ and $\hat{K}_h$ are the estimated values from Equation (15); B_d and K_d are the robot desired admittance.

To ensure the positive definiteness of robot admittance and control stability, the following constraints are added:

$$\begin{aligned} B_d(t) &= \begin{cases} \bar{B} - \hat{B}_h(t), & \text{if } \bar{B} - \hat{B}_h(t) \geq B_{\min}, \\ B_{\min}, & \text{otherwise,} \end{cases} \\ K_d(t) &= \begin{cases} \bar{K} - \hat{K}_h(t), & \text{if } \bar{K} - \hat{K}_h(t) \geq K_{\min}, \\ K_{\min}, & \text{otherwise.} \end{cases} \end{aligned} \quad (19)$$

where $B_{\min} > 0$ and $K_{\min} > 0$ are the lower-bound values of robot admittance, ensuring that the robot always exhibits positive definite damping and stiffness characteristics.

Through this adjustment law, the robot can adjust the desired admittance in real time to adapt to the dynamic changes in human impedance while ensuring the stability and safety of the interaction system.

3.2. Position Control

This section proposes a position controller design scheme aimed at enabling the robotic manipulator to exhibit desired admittance model characteristics. To address the issue of system model uncertainties, a model-free adaptive control (MFAC) strategy is adopted for controller design in this paper. The significant advantage of this MFAC controller lies in its utilization of only system input–output data without relying on precise mathematical models, thereby effectively overcoming the dependency of traditional control methods on model accuracy.

Consider the generalized control torques:

$$\tau_c = u_{MFAC} + \tau_{PD} - \tau_h, \quad (20)$$

where u_{MFAC} denotes the model-free adaptive control (MFAC) algorithm and τ_{PD} is an outer PD tracking loop.

Remark 5. The proposed controller given in Equation (20) consists of three parts. The first part is a model-free adaptive control (MFAC) algorithm, used to compensate for the uncertainties in the interaction system. The second part is a proportional-derivative (PD) controller, employed to stabilize the model tracking error. The last part is used to compensate for the human–robot interaction torque.

Next, substituting Equation (20) into Equation (1) yields

$$M(q)\dot{r} = -C(q, \dot{q})r + \tilde{\tau} - \tau_{PD}, \quad (21)$$

with

$$\tilde{\tau} = M(q)(\ddot{q}_r + \Lambda \dot{E}) + C(q, \dot{q})(\dot{q}_r + \Lambda E) + F(\dot{q}) + G(q) + \delta, \quad (22)$$

where $\tilde{\tau} = \bar{\tau} - u_{MFAC}$ is a function approximation error and $r = \dot{E} + \Lambda E$ is the mode error, where $E = q_r - q$, Λ is a positive parameter matrix.

Next, the MFAC algorithm is designed. Assume that the control inputs of model (22) are $u_{MFAC} = \bar{\tau}$ and the outputs are $y = q$. According to Property 1, $M(q)$ is an invertible matrix, and the state-space model of model (22) can be described as:

$$\dot{y} = -\frac{1}{\Lambda M(q)} u_{MFAC} - \frac{C(q, \dot{q})}{M(q)} y + \sigma, \quad (23)$$

where $\sigma = \frac{M(q)(\ddot{q}_r + \Lambda \dot{q}_r) + C(q, \dot{q})(\dot{q}_r + q_r) + F(\dot{q}) + G(q) + \delta}{\Lambda M(q)}$ represents other items.

If there exists a sampling period T such that $\dot{y}(\kappa) = \frac{y(\kappa+1) - y(\kappa)}{T}$, dynamics (23) in discrete time can be modeled as:

$$y(\kappa+1) = \left(I - \frac{TC(q, \dot{q})}{M(q)} \right) y(\kappa) - \frac{T}{\Lambda M(q)} u_{MFAC}(\kappa) + \sigma(\kappa). \quad (24)$$

The partial derivatives of $y(\kappa+1)$ with respect to outputs $y(\kappa)$ and control inputs $u(\kappa)$ are continuous, and model (24) satisfies the generalized Lipschitz. Let $\Delta \check{H}(\kappa) = (\Delta y(\kappa), \Delta u_{MFAC}(\kappa))^T$ and $\Psi(\kappa) = (\psi_1(\kappa), \psi_2(\kappa))$; an equivalent data model of model (25) is given in detail:

$$\Delta y(\kappa+1) = \psi_1(\kappa) \Delta y(\kappa) + \psi_2(\kappa) \Delta u_{MFAC}(\kappa), \quad (25)$$

where $\|\psi_i(\kappa)\| < b$, $i = 1, 2$.

Next, consider the following performance function:

$$J(\Delta u_{MFAC}(\kappa)) = \|y_d(\kappa+1) - y(\kappa+1)\|^2 + \lambda \|\Delta u_{MFAC}(\kappa)\|^2, \quad (26)$$

where $y_d(\kappa+1)$ represents outputs of the desired admittance model.

By substituting Equation (25) into Equation (26) and solving $\frac{\partial J(\cdot)}{\partial u_{MFAC}(\kappa)}$, one has

$$u_{MFAC}(\kappa) = u_{MFAC}(\kappa-1) + \frac{\rho \psi_2^T(\kappa)}{\|\psi_2(\kappa)\|^2 + \lambda} [y_d(\kappa+1) - y(\kappa) - \psi_1(\kappa) \Delta y(\kappa)], \quad (27)$$

where $\lambda > 0$, $\rho \in (0, 1]$.

Next, consider the following performance function to estimate the Pseudo-Partial Jacobian Matrix (PPJM) parameters:

$$J(\Psi(\kappa)) = \|\Delta y(\kappa) - \Psi(\kappa) \Delta \check{H}(\kappa-1)\|^2 + \zeta \|\Psi(\kappa) - \Psi(\kappa-1)\|^2. \quad (28)$$

By minimizing Equation (28), one gets

$$\hat{\Psi}(\kappa) = \hat{\Psi}(\kappa-1) + \frac{\vartheta [\Delta y(\kappa) - \hat{\Psi}(\kappa-1) \Delta \check{H}(\kappa-1)] \Delta \check{H}^T(\kappa-1)}{\|\Delta \check{H}(\kappa-1)\|^2 + \zeta}, \quad (29)$$

where $\zeta > 0$, $\vartheta \in (0, 2]$.

Combining control law (27) and the estimated PPJM parameters (29), the MFAC scheme is designed as follows:

$$\hat{\Psi}(\kappa) = \hat{\Psi}(\kappa-1) + \frac{\vartheta [\Delta y(\kappa) - \hat{\Psi}(\kappa-1) \Delta \check{H}(\kappa-1)] \Delta \check{H}^T(\kappa-1)}{\|\Delta \check{H}(\kappa-1)\|^2 + \zeta}, \quad (30)$$

$$u_{MFAC}(\kappa) = u_{MFAC}(\kappa - 1) + \frac{\rho \hat{\psi}_2^T(\kappa)}{\|\hat{\psi}_2(\kappa)\|^2 + \lambda} [y_d(\kappa + 1) - y(\kappa) - \hat{\psi}_1(\kappa) \Delta y(\kappa)], \quad (31)$$

where $\hat{\Psi}(\kappa) = \hat{\Psi}(1)$, if $[\hat{\Psi}(\kappa)] < \epsilon_1$ or $\text{sign}(\hat{\Psi}(\kappa)) \neq \text{sign}(\hat{\Psi}(1))$ and ϵ_1 is a small positive constant.

Remark 6. In MFAC scheme (30)–(31), model (22) is transformed and linearized for the MFAC algorithm, and the design of the controller only needs to utilize the I/O data without involving the unmodeled dynamics and relevant assumptions. Based on the above analysis, Theorem 1 is shown as follows.

Theorem 1. For model (22), if the parameters are chosen as $\lambda > 0$, $\zeta > 0$, $0 < \rho \leq 1$, and $s_0 < \vartheta \leq 2$, then MFAC scheme (30)–(31) with the desired signal $y_d(\kappa + 1) = y_d = \text{const}$, and model (22) guarantees that 1) $\lim_{\kappa \rightarrow \infty} \|y_d - y(\kappa + 1)\| = 0$ and 2) $\{y(\kappa)\}$, $\{u_{MFAC}(\kappa)\}$ are bounded.

A similar proof of Theorem 1 can be found in [8].

4. Simulation and Results

In this part, the robotic simulation model is built in Simulink using SolidWorks software 2023 SP3 and the SimMechanics toolbox (<https://ww2.mathworks.cn/help/sm/gs/simmechanics-first-and-second-generation-comparison.html> accessed on 23 July 2022) [35]. The mechanical device has five DOFs (shoulder: s_1 and s_2 ; elbow: e_1 ; wrist: w_1 and w_2). In this paper, three groups of simulation experiments are designed to test the proposed MFAC method and the performance of human–robot interaction, which are as follows: 4.1. Test of the position controller; 4.2. Test of impedance learning; 4.3. Test of the overall performance incorporating motion intention estimation. Interaction forces are acquired with force sensors mounted on the exoskeleton. We set the simulation time to $t = 4.5$ s. The specific details are as follows.

4.1. Test of Position Controller

In this simulation group of experiments, we verify the effectiveness of the proposed position control method by testing joint s_2 , and the other joints are fixed. In simulation experiments, the tracing performance of the proposed scheme is given, and results are compared with the NN adaptive control [27] and the adaptive sliding mode control (ASMC) scheme [36]. The parameters of the NN controller are set as $K_v = 5I$, $\Lambda = 20I$, $F = 100I$, and $\kappa = 0.3$. The parameters of the ASMC controller are set as $K_D = 5I$, $\Lambda = 2I$, and $\Gamma = 20I$. The parameters of the proposed MFAC method are set as $\rho = 0.01$, $\lambda = 10$, $\vartheta = 0.1$, $\zeta = 1$, $\hat{\psi}_{1,2}(1) = \text{diag}([1, 1, 1, 1, 1])$, $y(1) = y(2) = [0, 0, 0, 0, 0]^T$, $u(1) = u(2) = [0, 0, 0, 0, 0]^T$, $k_c = 1I$, and $\Lambda = 800I$. The tracking trajectory s_2 is given as $q_{d_2} = 0.1884 * t^2 - 0.02512 * t^3$. The disturbing force is described as $\delta = 0.5 \sin(t)$.

Result Analysis

Figures 2–4 present the comparative results of trajectory tracking performance of the neural network (NN) adaptive control method, the adaptive sliding mode control (ASMC) method, and the proposed method under external disturbance forces.

It can be observed from Figure 2 that when the system is subjected to external disturbances in the form of $\delta = 0.5 \sin(t)$, the tracking error (green dashed line e_2) of the NN method exhibits obvious fluctuations, with the error amplitude oscillating within approximately ± 0.05 rad, resulting in significant deviation between the actual trajectory (red dashed line q_2) and the desired trajectory (black solid line q_{d_2}). The NN method shows

relatively pronounced oscillations under disturbance, leading to substantial degradation of tracking accuracy.

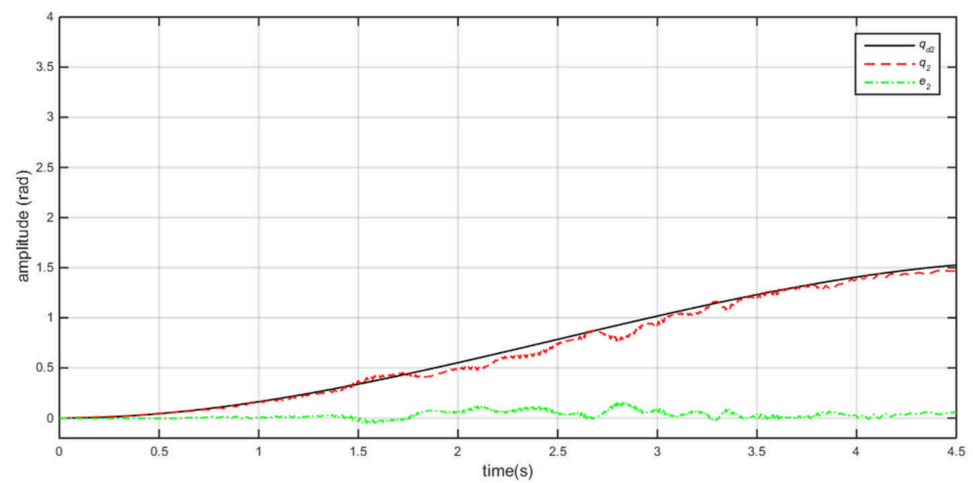


Figure 2. Simulation results of the NN adaptive control method.

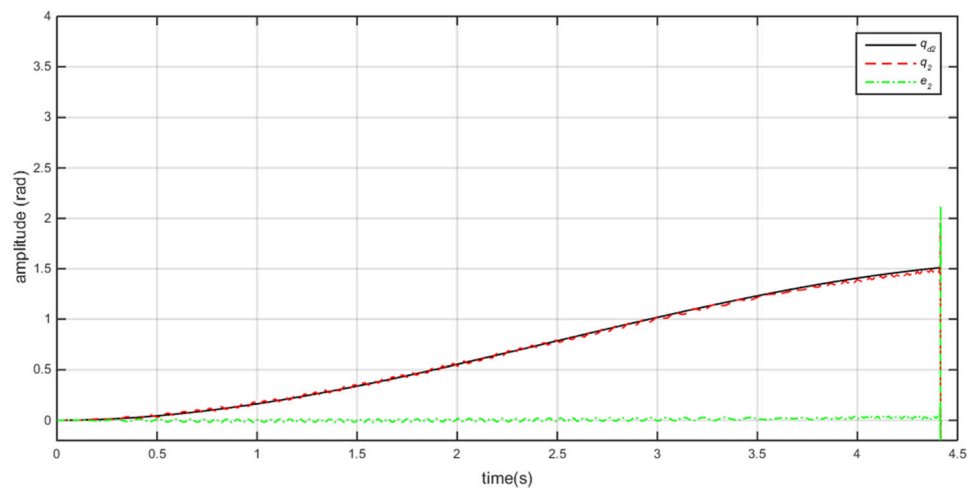


Figure 3. Simulation results of the ASMC method.

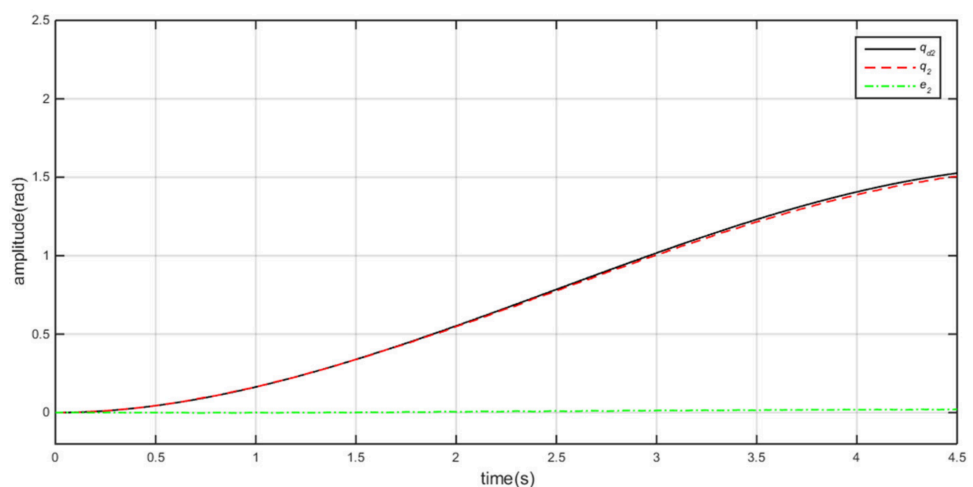


Figure 4. Simulation results of the proposed method.

As shown in Figure 3, the ASMC method demonstrates improved tracking performance compared with the NN method. The tracking error of the ASMC method is relatively

smaller, with reduced fluctuation amplitude. However, the ASMC method still exhibits certain chattering phenomena in the control input, which may cause mechanical wear and energy consumption in practical applications.

In contrast, as illustrated in Figure 4, the trajectory tracking curve of the proposed method is significantly smoother and more stable. The tracking error is maintained within a tighter bound of approximately ± 0.02 rad, and the error fluctuation amplitude is reduced by approximately 67% compared with the NN method and by approximately 45% compared with the ASMC method, without obvious periodic oscillations. The proposed method can effectively suppress the adverse effects of disturbances and maintain satisfactory tracking quality.

4.2. Test of Impedance Learning

In this group of simulation experiments, we tested the impedance learning performance of the proposed method and compared it with the performance of the variable admittance model. The proposed admittance adaptive method consists of two parts: in part 1, the two joints (w_1 and w_2) of the wrist are kept unchanged, and the other three joints (s_1 , s_2 , and e_1) are controlled in the inner loop by the proposed MFAC method; in part 2, the admittance controller is described as a spring–damper model, and the FFRLS method is used to obtain the parameters. To test the performance of the proposed method, a straight line is selected as the reference trajectory for the experiment. The reference trajectory of a straight line is taken as a line passing through the endpoint of the robot's hand, which is described as $x_d = 0.2t$, $y_d = 0.3t - 0.609$, $z_d = 0.4t + 0.235$, $t > 0$. The deflection angles of the posture and each axis are set to zero. The parameters of the proposed method are set as $\delta_0 = 10^3$, $\lambda_0 = 0.99$. The parameters of the variable admittance are set as $\bar{K} = 400 + 50\sin(0.5t)$, $\bar{B} = 1.8 + 0.5\sin(0.3t)$, simulating rhythmic muscle activation variations during cyclic training. The force information is shown in Figure 5. The simulation results are shown in Figure 6.

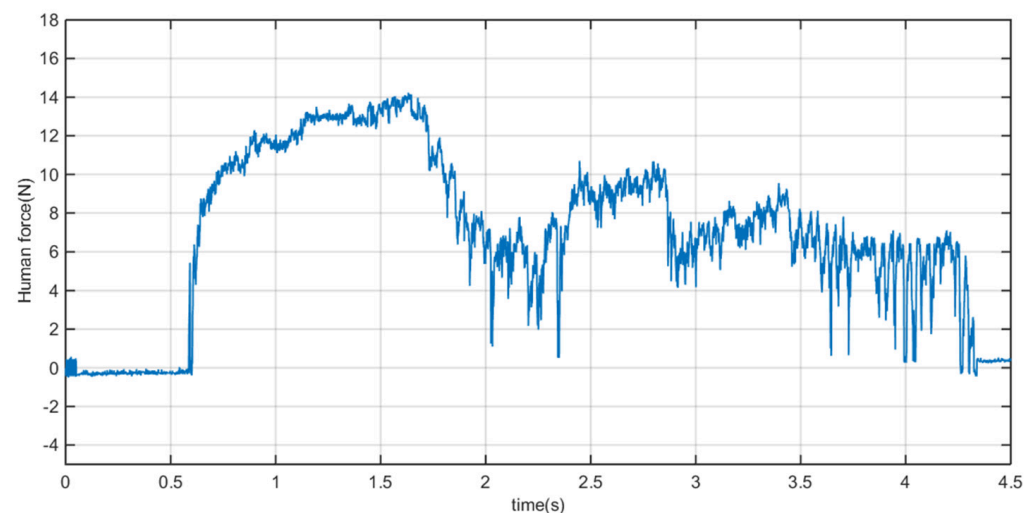


Figure 5. Force information of shoulder joint s_2 .

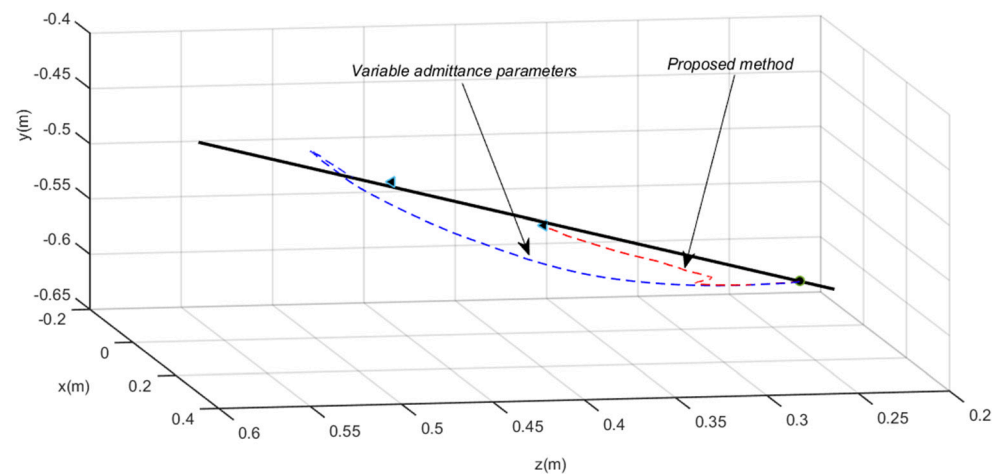


Figure 6. Simulation results of the variable admittance parameters and the proposed method.

Result Analysis

Figure 5 shows the performance comparison of two impedance learning methods: (1) variable admittance model and (2) the proposed method. The results demonstrate that the proposed method significantly outperforms the variable admittance model in tracking time-varying impedance parameters, which is mainly attributed to its online adaptive capability based on the FFRLS algorithm, fast convergence characteristics, and comprehensive stability guarantee mechanisms. Specifically, this method overcomes the limitation of the variable admittance model in adapting to the random time-varying characteristics of actual human impedance by real-time estimation of human time-varying impedance parameters ($\hat{B}_h, \hat{K}_h$) and dynamic adjustment of the robot desired admittance without relying on predefined sinusoidal curves or prior knowledge of environmental dynamics. The introduction of the forgetting factor $\lambda_0 = 0.99$ achieves an effective balance between historical data memory and sensitivity to new data, ensuring the fast tracking of time-varying parameters and avoiding the parameter adjustment lag problem of the variable admittance model. Meanwhile, the constraint conditions ($B_d \geq B_{min}$ and $K_d \geq K_{min}$) ensure that the robot impedance always maintains positive definiteness, effectively circumventing potential stability risks of the variable admittance model. Furthermore, this method only requires measurement of interaction force f_h and position information $X(t)$ without needing accurate human dynamic models, demonstrating stronger practical applicability and being more suitable for real human–robot interaction scenarios.

4.3. Test of the Overall Performance Incorporating Motion Intention Estimation

In this set of simulation experiments, we tested the overall effectiveness of the proposed scheme in this paper and selected the motion intention estimation corresponding to shoulder joint s_2 for the “shoulder abduction $0 \sim 90^\circ$ ” movement, where the force information is shown in Figure 6. The position control is implemented using the proposed MFAC method; the desired impedance model is achieved through the impedance learning strategy. Parameter settings are given in Sections 4.1 and 4.2. The simulation results are shown in Figure 7.

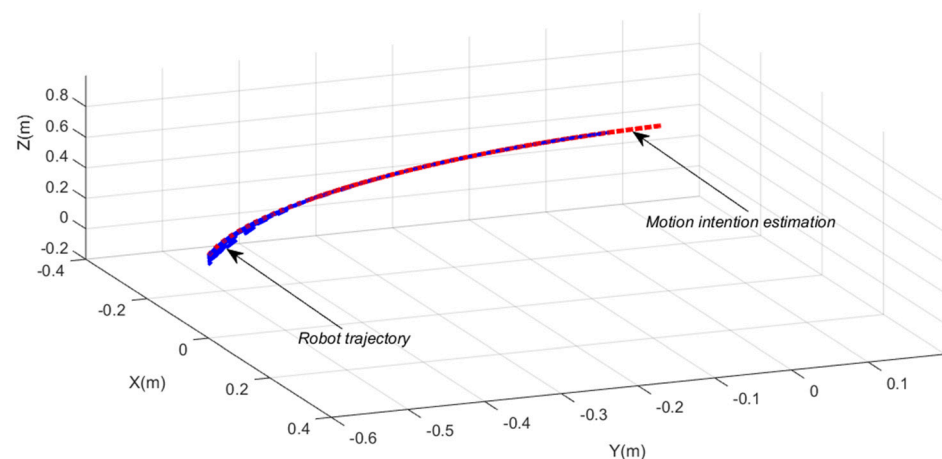


Figure 7. Simulation results for the “shoulder abduction $0 \sim 90^\circ$ ” movement corresponding to shoulder joint s_2 .

Result Analysis

As shown in Figure 7, in the simulation experiment of shoulder joint s_2 for the “shoulder abduction $0 \sim 90^\circ$ ” movement, the proposed scheme demonstrates favorable motion intention estimation and tracking performance. The robot actual trajectory (blue solid line) and motion intention estimation (red dashed line) maintain high consistency throughout the entire motion process, indicating that the MFAC position control method can effectively achieve the precise tracking of desired motion intention. The trajectory morphology conforms to the biomechanical characteristics of human shoulder abduction: the curvature changes significantly in the initial stage, corresponding to the starting acceleration process, and then gradually becomes smooth and stable. With the desired impedance model realized through the impedance learning strategy, the robot can adapt to interaction force variations while tracking motion intention, ensuring trajectory continuity and compliance, and avoiding tracking deviations caused by abrupt stiffness changes. These results validate the feasibility and effectiveness of the proposed method in human motion assistance and rehabilitation robot applications.

5. Conclusions

This paper proposes a safe and effective control framework for human–robot physical interaction with exoskeleton robots. The framework achieves real-time estimation of human motion intention through a model-free adaptive control method, employs the Forgetting Factor Recursive Least Squares (FFRLS) method for online estimation of time-varying human impedance parameters, and combines it with a model-free adaptive trajectory tracking control strategy to optimize interaction performance. Simulation results demonstrate that the proposed control framework significantly outperforms conventional methods in terms of safety and compliance, effectively enhancing the exoskeleton robot’s adaptability to human motion. Future work will focus on experimental validation of this framework on real exoskeleton systems and further investigation of control strategy optimization in complex human–robot interaction scenarios.

For future work, both technical and practical aspects will be addressed. On the theoretical side, given the application scenario in stroke rehabilitation, practical factors such as sensor noise, actuator delay, individual patient variability, and safety constraints need to be taken into consideration to further optimize the proposed strategy; on the practical aspect, with dedicated rehabilitation robot equipment, physical experiments will be conducted and compared with simulation results to further optimize the control strategy.

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