Design of RBFNN-Based Adaptive Sliding Mode Control Strategy for Active Rehabilitation Robot

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ABSTRACT In accordance with the movement coordination principle of both lower limbs, a complete radial basis functions neural network based adaptive sliding mode control strategy (RBFVSMC) is proposed. The movement information on the non-affected side of patients is detected to drive the rehabilitation training. The nonlinear mathematical model of the rehabilitation robot system is firstly described. Based on the robotic dynamic model, a variable sliding mode control (VSMC) is proposed to stabilize the system. To reduce the buffeting problem caused by VSMC, the universal approximation of RBFNN is used to approach and compensate external disturbances and uncertainties. Besides, the buffeting phenomenon of sliding mode control is alleviated by replacing the sign function with a saturation function. The final asymptotic stability is guaranteed with Lyapunov criteria. Compared to proportional-integral-derivative (PID), radial basis functions neural network (RBFNN), continuous terminal SMC (CNTSMC), and decentralized adaptive robust controller (NDOBCTC), the effectiveness of the overall control scheme is demonstrated by co-simulation and human experiment in accordance to track following performance and disturbances rejection ability.

INDEX TERMS Rehabilitation robot, radial basis functions neural network, variable sliding mode control, coordinated movement.

I. INTRODUCTION

The incidence of stroke is increasing with aging. Stroke has become one of the most serious diseases for humans in the world, and its incidence is significantly higher in developed countries than in developing countries. The stroke could lead to the damage of the human nervous system and the disorder of limb behavior, even hemiplegia. However, timely rehabilitation training could help patients to form gait memory in the cerebral cortex and re-establish the connection between central nerves and limbs of injury, and recover the brain injury sites through gradual stimulation. Compared with the traditional manual assistance of rehabilitation doctors, as an important branch of the medical robot, rehabilitation robots could effectively and economically provide rehabilitation treatment for patients with physical disabilities.

At present, the research on the lower limb rehabilitation robot mainly focuses on the symmetrical bilateral lower limb rehabilitation training equipment [1]–[3], which lacks specifically control strategy for stroke patients with unilateral dyskinesia. Therefore, it is necessary to study a control strategy to help stroke patients with active rehabilitation training.

Due to the highly nonlinear dynamical situation of rehabilitation robots, the control strategy is needed to satisfy the characteristic of coordination. Owing to the convenience of application, PID control has been widely implemented to robotic manipulators. However, for systems with nonlinear and time-varying, it is difficult to establish accurate mathematical models. And conventional PID controllers cannot achieve ideal control effect. To realize the good performance, many advanced control technologies have been proposed, such as adaptive control [4], [5], computational torque control [6], [7], fuzzy control [8], and sliding mode control (SMC) [9]–[12]. Among these control techniques, SMC has received extensive attention due to its significant robustness to uncertainty and interference [13], [14]. SMC is suitable for robotic control, firstly, it does not prescribe an accurate mathematical model of the controlled object. Secondly, SMC is insensitive
to external disturbances and change of parameters. The output of system could track the desired instruction directly through the synovial controller. However, since the current state reaches the synovial surface, it is difficult to slide along the synovial surface strictly towards the equilibrium point, but crosses back and forth on both sides of the synovial surface, resulting in buffeting. To overcome the problem of buffeting, many scholars have considered the method of anti-buffeting. Representative research methods include quasi-sliding mode square, approach rate method, interference observer method, and neural network method. Chenghu Jing et al. proposed a continuous nonsingular terminal SMC (CNTSMC) [15]. This method could suppress buffeting effectively and achieve finite-time convergence, but the convergence of the tracking error was not good enough in the case of bounded disturbance. The combination of SMC and interference estimation is a potential concept [16]–[22]. Non-linear interference observer (NDO) is a common classic method. Because of its simple design and convenient implementation, it is used to solve various practical problems in control engineering. In [23], an adaptive sliding mode disturbance observer was proposed. Based on the disturbance observer, a composite control with specified performance was developed for the space manipulator. In [19], a decentralized adaptive robust controller (NDOBCTC) based on NDO was proposed for robot manipulators. However, these control methods based on disturbance observer only achieve asymptotic stability, which means that the tracking error cannot be converged to an equilibrium state within a finite time. The universal approximation method of a neural network was used to compensate for external disturbances and uncertainties, or to approach the switching part of the sliding mode controller. The discontinuous control signal was changed to the continuous, which could effectively reduce the buffeting problem. Compared with other types of neural networks (NNs), such as Markovian NNs [24], [25], Hopfield NNs [26], radial basis function (RBF) is simple and smooth. The perfect approximation ability of RBF helps to improve the robustness of the control system [27]–[29] and to deal with periodic disturbances [31].

Therefore, in this article, a RBFNN-based adaptive sliding mode control strategy is proposed. The contributions of this article are summarized as follows:

1) To the best of our knowledge, this article might be the first work to propose the active lower limb rehabilitation training strategy based on motion data of non-affected side to drive dyskinetic side during motion control process.

2) A novel rehabilitation robot was designed. On the premise of enough stiffness, carbon-fibre material was adopted to realize the lightweight design, with the overall weight reduced by 25%. And the nonlinear mathematical model of lower limb robot system was constructed.

3) A complete RBF-based adaptive sliding mode control scheme was developed. Specifically, the control scheme adopted global sliding surface. The nonlinear mapping capability of neural network was combined with the characteristics of sliding mode control. The uncertain upper bound of the system was determined by the adaptive learning ability of RBFNN. Furthermore, in order to alleviate the chattering phenomenon of conventional sliding mode control, the sign function was substituted by saturation function in control algorithm.

4) Both simulation results and human experiment results on the proposed rehabilitation robot demonstrated the effectiveness and superiority of the proposed control scheme for achieving desired performance of track following in terms of accuracy, and robustness against disturbances.

The rest of this article is organized as follows. The proposed rehabilitation robot and nonlinear mathematical model of the robot are described in Section II. Section III presents the complete RBF-based adaptive sliding mode control strategy design procedure. Simulation results are given in Section IV. In Section V, human experiments in terms of track following performance and disturbances rejection ability are implemented. Finally, Section VI concludes this article.

II. PROPOSED REHABILITATION ROBOT SYSTEM

A. THE DESIGN OF PROPOSED ROBOT

The developed lower limb exoskeleton is shown in Fig.1. For each leg, it has an active degree of freedom (DoF) for hip joint and knee joint respectively, and a passive DoF for ankle joint. The length of the range for thigh bar and shank bar is 402 mm to 505 mm and 397 mm to 506 mm, respectively. The subject will be fixed by straps, and exoskeleton could lead human limbs to perform rehabilitation training. The non-affected lower extremity exoskeleton is unpowered, and equipped with the encoder in each joint for extraction of joint angle. The hip joint and knee joint of the dyskinetic side lower extremity exoskeleton are driven by direct current servo motor, whereas the ankle joint adopted passive reset function.
There was a detailed description of the exoskeleton in the preliminary study [32]. The dynamic simulation of the designed lower limb exoskeleton system is conducted through ADAMS, as shown in Fig. 2. The force on thigh and calf changes in three axes over time is shown in Fig. 3. During a gait cycle, the maximum force on the thighs and calf is 950N and 650N, respectively. Through the dynamic analysis of the lower extremity exoskeleton system, the driver of hip joint and knee joint adopted the servo motor with a rated power of 460W. The length of the ball screw is 4mm, the rated thrust is 2000N, the maximum linear speedup is 100mm/s, which is sufficient for assisting people in rehabilitation training. The step function is utilized to control the speed of the ball screw. The linear motion of the ball screw is transformed into the rotational motion of the hip joint and knee joint in the sagittal plane, which approximately fits the normal gait of a human. The speed of the ball screw is input to make the lower limb exoskeleton exercise in accordance with the approximated normal human gait. The driving force of the given motion is deduced to verify whether the thrust in the previous stage is enough. The stretch and contract of thigh, calf and waist adopted stepless adjustable mechanism. To ensure the lightweight of the robot, the carbon-fiber material and aluminum alloys are adopted. The thigh, calf and waist are made of carbon fiber instead of the aluminum alloys. Compared to the overall structure of all aluminum alloys, the weight is reduced by 25%. This exoskeleton leg fits patients from 1.50m to 1.90m tall, which covers more than 99% of corresponding adults, with maximum body weight of 100kg.

**B. REHABILITATION ROBOT MODEL**

Considering that the ankle joint has only one passive degree of freedom, for the sake of analysis, the proposed lower limb robot model is simplified to two-joint robot system, as shown in Fig.4. The nonlinear dynamic equation of rehabilitation robot is described as follows:

\[
H(\theta)\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + G(\theta) + F(\theta, \dot{\theta}, \ddot{\theta}) = \tau - \tau_d \quad (1)
\]

where \( \theta, \dot{\theta}, \ddot{\theta} \in \mathbb{R}^n \) are the joint angular displacement vector, angular velocity vector, and angular acceleration vector respectively, \( H(\theta) \in \mathbb{R}^{n \times n} \) is symmetric positive definite inertia matrix, \( C(\theta, \dot{\theta}) \in \mathbb{R}^{n \times n} \) is Coriolis force and Centrifugal force vector, \( G(\theta) \in \mathbb{R}^n \) is gravity term vector, \( F(\theta, \dot{\theta}, \ddot{\theta}) \) is frictional force. \( \tau \in \mathbb{R}^n \) is input vector of joint control torque, \( \tau_d \) is random interference signal.

where

\[
H(\theta) = \begin{bmatrix}
a + b + 2c_2d & b + 2c_2d \\
b + 2c_2d & b
\end{bmatrix}
\]

\[
C(\theta, \dot{\theta}) = \begin{bmatrix}
-d\dot{\theta}_1s_2 & -d(\dot{\theta}_1 + \dot{\theta}_2)c_2 \\
d\dot{\theta}_1s_2 & 0
\end{bmatrix}
\]

\[
G(\theta) = \begin{bmatrix}
g'c_1 + dg'c_{12} \\
g'dc_{12}
\end{bmatrix}
\]

\[
F(\theta, \dot{\theta}, \ddot{\theta}) = 0.02\text{sign}(\dot{\theta})
\]

where \( g' = \frac{g}{L_1}, a = (m_1 + m_2)L_1^2, b = m_2L_2^2, d = m_2L_1L_2, c_i = \cos(\theta_i), s_i = \sin(\theta_i), c_{12} = \cos(\theta_1 + \theta_2), m_1 \) and \( m_2 \) are the weight of thigh and calf respectively, \( L_1 \) and \( L_2 \) are the length of thigh and calf respectively.
nonlinear functions. The radial basis function is responsive to the local input signal. That is when the input signal is near the center of the basis function, the hidden layer node would produce a larger output, whereas the output layer node is usually the simplest linear function.

C. RBF-based ADAPTIVE SLIDING MODE CONTROL STRATEGY (RBFVSMC)

The nonlinear dynamic equation of rehabilitation robot is set as:

$$H(\theta)\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + G(\theta) + F(\theta, \dot{\theta}, \ddot{\theta}) = \tau - \tau_d$$  \hspace{1cm} (2)

The robot system has the following two properties.

Property 1: The inertial matrix $H(\theta)$ is symmetrical, positive definite and bounded. And the inverse matrix $H^{-1}(\theta)$ existed.

Property 2: $\dot{H}(\theta) - 2C(\theta, \dot{\theta})$ is skew symmetric matrix, that is, any vector $x$ satisfies that

$$x^T [\dot{H}(\theta) - 2C(\theta, \dot{\theta})] x = 0$$ \hspace{1cm} (3)

Assumption 1: The random interference signal $\tau_d$ is bounded, and satisfying $||\tau_d|| \leq T_0$, where $T_0$ is positive number.

The tracking error and velocity error are expressed as

$$e = \theta - \dot{\theta}, \quad \dot{e} = \dot{\theta} - \ddot{\theta}$$ \hspace{1cm} (4)

where $\theta$ and $\dot{\theta}$ are desired joint position vector and velocity vector, and $\ddot{\theta}$ are real joint position vector and velocity vector.

For system (1), the following integral sliding mode surface is chosen as:

$$s = \dot{e} + \alpha e - p(t)[\dot{e}(0) + \alpha e(0)]$$ \hspace{1cm} (5)

where $\alpha$ is integer, $p(t) = \exp(-\beta t)$, $\beta$ is positive number.

Differentiating $s$ with respect to time along the system (1) yields

$$\dot{s} = \ddot{e} + \alpha \dot{e} - \ddot{p}(t)[\dot{e}(0) + \alpha e(0)]$$ \hspace{1cm} (6)

From (1) and (6), the following equation can be obtained.

$$Hs = H[\ddot{e} + \alpha \dot{e} - \ddot{p}(t)[\dot{e}(0) + \alpha e(0)]]$$

$$= H[\dot{\theta}_d - \ddot{\theta} + \alpha \dot{e} - \ddot{p}(t)[\dot{e}(0) + \alpha e(0)]]$$

$$= H[\dot{\theta}_d + \alpha \dot{e} - \ddot{p}(t)[\dot{e}(0) + \alpha e(0)]] - H\ddot{\theta}$$

$$= H[\dot{\theta}_d + \alpha \dot{e} - \ddot{p}(t)[\dot{e}(0) + \alpha e(0)]] - \tau + \tau_d + G(\theta)$$

$$+ F(\theta, \dot{\theta}, \ddot{\theta}) - C(\theta, \dot{\theta})s + C(\theta, \dot{\theta})$$

$$\times \{\dot{\theta}_d + \alpha \dot{e} - \ddot{p}(t)[\dot{e}(0) + \alpha e(0)]\}$$

$$= -C(\theta, \dot{\theta})s - \tau + \tau_d + f(x)$$ \hspace{1cm} (7)

where the uncertain term $f(x)$ can be exactly described as

$$f(x) = H[\dot{\theta}_d + \alpha \dot{e} - \ddot{p}(t)[\dot{e}(0) + \alpha e(0)]] + G(\theta) + F(\theta, \dot{\theta}, \ddot{\theta})$$

$$+ C\{\dot{\theta}_d + \alpha \dot{e} - p(t)[\dot{e}(0) + \alpha e(0)]\}$$ \hspace{1cm} (8)

The RBFNN is used to approximate $f(x)$. The state variable $x$ is defined as

$$x = [\dot{e}, \ddot{e}, \dot{\theta}_d, \ddot{\theta}_d, \dddot{\theta}_d]$$
In order to stabilize the system, the control law is designed as follows:

\[ \tau = H^{-1} \left( \frac{v}{s} \right) + f(x) + K_v s \]

(9)

where \( K > \eta + \|F(\bar{\theta}, \bar{\theta})\| \), \( \eta > 0 \), \( K_v \) is positive-definite matrix. \( \hat{f}(x) \) is output of RBFNN.

The following Lyapunov function candidate is chosen as:

\[ V = \frac{1}{2} s^T H(\theta)s \]

(10)

Differentiating the Lyapunov function candidate (10) with respect to time along the system (1).

\[ \dot{V} = s^T H \dot{s} + \frac{1}{2} s^T \dot{H} s \]

\[ = s^T (-C(\theta, \dot{\theta})s - \tau + \tau_d + f(x)) + \frac{1}{2} s^T \dot{H} s \]

\[ \leq -H^{-1}(\theta) K \frac{s}{s} + s^T \dot{x}_0 - s^T K_v s \]

(12)

where \( f(x) = f(x) - \hat{f}(x), \dot{x}_0 = \hat{f}(x) + \tau_d. \)

It can be seen from equation (12) that the stability of the control system depends on \( \dot{x}_0 \), which is equivalent to the size of approximated accuracy \( \hat{f}(x) \) and \( \tau_d. \)

In this article, the uncertain term \( f(x) \) is approximated by RBFNN.

The algorithm of RBFNN is

\[ \varphi_i(x) = \exp\left(-\frac{\|x - c_i\|^2}{\sigma_i^2}\right), \quad i = 1, 2, \ldots, n \]

(13)

\[ f(x) = W^T \varphi(x) + \varepsilon \]

(14)

where \( x \) is the input of RBFNN, where \( c_i \) and \( \sigma_i \) are the center vector and the width of hidden layer, respectively. \( \varphi(x) \) is the Gaussian radial basis functions; \( W^* \) is the ideal network weights for approximating \( f(x) \). \( \varepsilon \) is the approximation error of network.

The output of RBFNN is

\[ \hat{f}(x) = W^T \varphi(x) \]

(15)

Then

\[ \dot{x}_0 = \hat{f}(x) + \tau_d = \dot{W}^T \varphi(x) + \varepsilon + \tau_d \]

(16)

where \( \dot{W} = W^* - \dot{W}, \|W^*\|_F \leq W_{\text{max}}. \)

The control is re-defined as

\[ \tau = H^{-1}(\theta) K \frac{s}{s} + \hat{f}(x) + K_v s - v \]

(17)

where \( v \) is robust item which is used to overcome the approximated error \( \varepsilon \) and interference \( \tau_d. \)

The robust item is expressed as

\[ v = -(\varepsilon_N + T_0) \text{sign}(s) \]

(18)

where \( \varepsilon \leq \varepsilon_N, s \in \mathbb{R}^n. \)

\[ \text{sign}(s) = \begin{cases} \frac{s}{\lambda}, & |s| \leq \lambda \\ \text{sign}(s), & |s| > \lambda \end{cases} \]

(19)

where \( \lambda \geq 0. \)

Hence, the robust item is defined as

\[ v = -(\varepsilon_N + T_0) \text{sign}(s) \]

(20)

The following Lyapunov function candidate is chosen as:

\[ V = \frac{1}{2} s^T H(\theta)s + \frac{1}{2} \text{tr}(\dot{W}^T \delta^{-1} \dot{W}) \]

(21)

where \( \delta \) is positive-definite matrix, and the inverse matrix \( \delta^{-1} \) existed.

Differentiating the Lyapunov function candidate (21)

\[ \dot{V} = s^T H \dot{s} + \frac{1}{2} s^T \dot{H} s + \text{tr}(\dot{W}^T \delta^{-1} \dot{W}) \]

(22)

Substituting (22) into the control law (17) yields

\[ \dot{V} = s^T (-C(\theta, \dot{\theta})s - \tau + \tau_d + f(x)) + \frac{1}{2} s^T \dot{H} s \]

\[ + \text{tr}(\dot{W}^T \delta^{-1} \dot{W}) \]

\[ = s^T \dot{W}^T \delta^{-1} \dot{W} \]

(23)

In view of the property 2,

\[ \dot{V} = s^T (-H^{-1}(\theta) \frac{K s}{s} + \hat{f}(x) - K_v s + \tau_d + v) \]

\[ + \text{tr}(\dot{W}^T \delta^{-1} \dot{W}) \]

\[ = -s^T K_v s - \text{tr}(H^{-1}(\theta) K s) + s^T (\varepsilon + \tau_d + v) \]

(24)

The characteristics of the robot is taken into consideration, the network adaptive law is set as

\[ \dot{W} = -\eta \varphi \dot{x}^T \]

(25)

Then

\[ \dot{V} = -s^T K_v s - s^T (\varepsilon + \tau_d + v) \]

(26)

It can be observed from equation (14).

\[ s^T (\varepsilon + \tau_d + v) = s^T (\varepsilon + \tau_d) + s^T v \]

\[ = s^T (\varepsilon + \tau_d) - \|s\| (\varepsilon_N + \tau_d) \leq 0 \]

(27)

Hence, \( \dot{V} \leq 0 \), which shows that the system is asymptotic stability.
IV. CO-SIMULATION WITH MATLAB

To validate the proposed approach, co-simulation experiments are realized through SolidWorks and MATLAB/Robotics Toolbox. The exoskeleton prototype in SolidWorks is imported into MATLAB/Simulink, and the process of co-simulation is shown in Fig. 6. The Robotics Toolbox is used for joint simulation. The lower extremity exoskeleton could be described through an m file in MATLAB, which contained the physical parameters of the exoskeleton. In the simulation model, the input signal is the trajectory of knee joint generated by MATLAB according to human gait characteristics.

Considering the uncertainties of system, the actual value of the system could not be accurately obtained. The nominal values of the system parameters used for controller design are $m_{10} = 0.6$ and $m_{20} = 0.6$. The time-varying external disturbances are assumed to be $r_d = \text{rand}(1,2)$. In the simulation, the reference trajectory of knee joint is approximated to $q_{d1} = 1.1 \sin(t + 1.34)$. The initial state of the system is set as $q_1(0) = 0.8, \dot{q}_1(0) = 0$. The input of RBFNN is $x = [e^T, \dot{e}^T, \dot{\theta}_d, \ddot{\theta}_d]$. In the robust term, $\epsilon_N = 0.50, T_0 = 0.50$, the initial value of a Gaussian-base function parameter is $[-3, -2, -1, 0, 1, 2, 3]$. The parameters of controller are set as $K_v = \text{diag}(15, 15), \eta = \text{diag}(10, 10), \alpha = -10, \beta = 5$. The controller is shown in equation (17), and the adaptive law is equation (25). And the width $\sigma_i$ and the center of RBFNN are chosen as

$$\sigma_i = 1000, \quad i = 1, 2, 3$$

$$c = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -420 & 0 & 420 \\ -280 & 0 & 280 \end{bmatrix}$$

In the simulation experiment, the experimental results of position tracking and speed tracking of knee joint are shown in the Fig. 7. The red line is standard gait trajectory, and the blue line is the actual trajectory. The relative mean position error and speed error of knee joint are 0.23 rad and 0.27 rad/s respectively. The time from the initial state to the tracking error less than 0.2 rad is 0.53s. The speed tracking error was adjusted to less than 0.3 rad/s in 1.32s. The phase trajectories of trace error are shown in Fig. 8 and Fig. 9. When the VSMC reaches the sliding mode surface, it approaches the equilibrium point along the sliding mode surface.

However, the chattering of the controller at the equilibrium point is severe. The chattering problem is effectively reduced by adaptive adjustment of proposed RBFVSMC. In order to reduce chattering, the saturation function $\text{sat}(s)$ is used to replace the symbol function $\text{sign}(s)$. The simulation results are shown in the Fig. 10 and Fig. 11. It can be seen that the chattering of the control input is significantly reduced and the input signal is smoother. According to Fig 12, the output produced by the controller proposed in this article is stable. In summary, the controller could track the trajectory accurately, and it has strong robustness. However, the scheme has great fluctuation at the initial moment, and it needs further study and improvement in the future.
V. EXPERIMENT

Human experiments are conducted to demonstrate the functionality of the new system. The rehabilitation robot platform is shown in Fig. 13. The exoskeleton is designed according to the statistics in which the normal ranges of walking are about 20° in flexion and 40° in extension for the hip joint, and about 70° in flexion and 0° in extension for the knee joints, and about 0° in planter flexion and 20° in dorsiflex for ankle joints. The specifications are not only applicable for walking on level ground, but also could satisfy slope and stairs. However, the influence of terrains such as slope or stairs is not considered in this study. The control system consists of the data processor Raspberry Pi and the motion controller STM32F103. Raspberry Pi is used to process data collected from encoders (AD36/1217AF. ORBVB, Hengstler, Germany). The communication mode between data processor and motion controller is parallel port communication. Motion controller is used to control the motors through the Controller Area Network (CAN) Fieldbus. The encoder 1 and encoder 2 are used to acquire the movement data of the hip joint, and encoder 3 and 4 together record the angle of knee joint. When the non-affected side is walking, the sensor data are transmitted to the data processor for processing and forming a gait movement trajectory. Then the controller will instruct the dyskinesia side to follow the movement trajectory.

A healthy subject with the age of 25, the weight of 68kg, and the height of 170cm is recruited for the follow-up experiment. A written consent is obtained from him. The subject is instructed to perform normal walking exercises on the ground. For safety reasons, if the angle of the exoskeleton is greater than the allowable value, the exoskeleton will be forced to stop moving by software. In addition, the subjects could shou off the power through emergency switch button if they need to do it at any time, as shown in Fig. 14.
TABLE 1. The parameters of each controller.

| Method     | Parameters                                                                 |
|------------|----------------------------------------------------------------------------|
| PID        | \( K_p=1.5, K_i=0, K_d=3 \)                                               |
| RBFNN      | \( \omega=[-0.5,0.3,-0.5,0.3,0.4,0.2], \xi=[-1.0 -0.5 0.5 1.0] \)       |
| CNTSMC     | \( \gamma=\gamma=1.5, \beta_1=\beta_2=0.1, \rho_1=\rho_2=0.5, K_r=K_d=\text{diag}\{100,100\} \) |
| NDOBCTC    | \( K_v=\text{diag}\{22,22\}, K_p=\text{diag}\{100,100\}, X=\text{diag}\{0.01,0.01\} \) |

FIGURE 15. Comparison diagram of position tracking for hip joint.

FIGURE 16. Comparison diagram of speed tracking for hip joint.

FIGURE 17. Comparison diagram of position tracking for knee joint.

To verify the effectiveness of the proposed method, the results of the simulation are compared with those of the CNTSMC [10], NDOBCTC [19]. And the parameters of each control method are set just as shown in the table 1. The good agreement between the reference trajectory and the actual trajectory illustrates the effectiveness of the measurement and control method. The figure for the joint position and motion velocity of the hip joint and the knee joint is shown in the Fig. 15- Fig.18, respectively. The overall average error is shown in the table 2. The experimental results show that the tracking performance of the RBFNNVSMC controller designed in this article is better, and the overall average error of hip joint position, hip joint speed, knee joint position, and knee joint speed is 1.123 rad, 0.179 rad, 1.103 rad, and 0.307 rad respectively. And the biggest error generated during the whole exercise is 1.613 rad/s, 0.981 rad/s, 2.990 rad/s, and 1.219 rad/s, which basically meets the training requirements of the lower limb rehabilitation robot.

VI. CONCLUSION

According to the principle of the coordination of the lower limbs of the human body, the characteristics of one limb with motor function of the stroke patient are fully utilized. The rehabilitation training of dyskinetic side is driven by the perception and detection of the lower limb movement information of the non-affected side of the patients.

In this work, a complete RBFNN-based adaptive sliding mode control strategy is designed to help stroke patients conduct the autonomous rehabilitation training. This article aims to enhance the accuracy, and robustness of trajectory tracking for lower limb robot system. To this end, the nonlinear mathematical model of rehabilitation robot is deduced. Furthermore, an RBFNN-based adaptive chattering reduction of sliding mode control method is proposed. In addition, the sign function in control system is replaced by saturation function in order to reduce the chattering.

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of sliding mode control method is proposed. In addition, the sign function in control system is replaced by saturation function in order to reduce the chattering phenomenon of sliding mode control. And a sufficient condition for the stability of the system is given based on Lyapunov theorem. Finally, simulation test and human experiments are carried out to demonstrate the effectiveness of the proposed control strategy compared with PID, RBFNN, CNTSMC, and NDOBCTC, namely higher trajectory tracking accuracy and stronger disturbances rejection ability.

In the following study, to achieve unmeasured states recovery, an extended state observer will be designed for not only recovering unmeasured states but also estimating the output disturbances in real time. And other performance index should be taken into consideration, such as the range of potential energy [33], fault-tolerant [34]. Due to the lack of experimental conditions that could detect the internal rehabilitation of human lower limbs, our current results cannot directly evaluate the actual use of human rehabilitation. For this reason, further testing should be considered in collaboration with doctors in the clinical laboratory.

REFERENCES

[1] W. Meng, Q. Liu, Z. Zhou, Q. Ai, B. Sheng, and S. Xie, “Recent development of mechanisms and control strategies for robot-assisted lower limb rehabilitation,” *Mechatronics*, vol. 45, no. 4, pp. 132–145, 2015.

[2] T. G. Sugar, D. Armstrong, B. Najafi, S. Redkar, J. A. Ward, S. Bai, G. S. Virk, and T. Sugar, “Low-limb wearable robotics,” in *Wearable Exoskeleton Systems: Design, Control and Applications*, London, U.K.: Institution of Engineering and Technology, 2018, pp. 5–16.

[3] K. H. Low, “Robot-assisted gait rehabilitation: From exoskeletons to gait systems,” in *Proc. Defense Sci. Res. Conf. Expo*, Singapore, Aug. 2011, pp. 1–10.

[4] R. Sharma, P. Gaur, and A. P. Mittal, “Performance analysis of two-degrees of freedom fractional order PID controllers for robotic manipulator with payload,” *ISA Trans.*, vol. 58, no. 6, pp. 79–91, 2015.

[5] H. Wang, “Adaptive control of robot manipulators with uncertain kinematics and dynamics,” *IEE Trans. Autom. Control*, vol. 62, no. 2, pp. 48–54, Feb. 2017.

[6] N. Nikdel, M. Badamchizadeh, V. Azimirad, and M. A. Nazari, “Fractional-order adaptive backstepping control of robotic manipulators in the presence of model uncertainties and external disturbances,” *IEEE Trans. Ind. Electron.*, vol. 63, no. 10, pp. 49–56, Oct. 2016.

[7] P. Masarati, “Computed torque control of redundant manipulators using general-purpose software in real-time,” *Multibody Syst. Dyn.*, vol. 32, no. 4, pp. 403–428, Dec. 2014.

[8] L. Angel and J. Viala, “Tracking control for robotic manipulators using fractional order controllers with computed torque control,” *IEEE Latin Amer. Trans.*, vol. 6, no. 7, pp. 84–91, Jul. 2018.

[9] J. Shi, H. Liu, and N. Bajcinca, “Robust control of robotic manipulators based on integral sliding mode,” *Int. J. Control*, vol. 81, no. 10, pp. 1537–1548, Oct. 2008.

[10] S. Yu, X. Yu, and B. Shirinzadeh, “Continuous finite-time control for robotic manipulators with terminal sliding mode,” *Automatica*, vol. 41, no. 11, pp. 26–45, 2005.

[11] M. Zhihong, A. P. Paplinski, and H. R. Wu, “A robust MIMO terminal sliding mode control scheme for rigid robotic manipulators,” *IEEE Trans. Autom. Control*, vol. 39, no. 12, pp. 64–69, Dec. 1994.

[12] D. Zhao, S. Li, and F. Gao, “A new terminal sliding mode control for robotic manipulators,” *Internet J. Control*, vol. 78, no. 4, pp. 32–45, 2009.

[13] M. Chen, Q.-X. Wu, and R.-X. Cui, “Terminal sliding mode tracking control for a class of SISO uncertain nonlinear systems,” *IEEE Trans.*, vol. 52, no. 2, pp. 198–206, 2013.

[14] Y. Wang, Y. Gao, H. R. Karimi, H. Shen, and Z. Fang, “Sliding mode control of fuzzy singularly perturbed systems with application to electric circuit,” *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 10, pp. 67–75, Oct. 2018.

[15] C. Jing, H. Xu, and X. Niu, “Adaptive sliding mode disturbance rejection control with prescribed performance for robotic manipulators,” *ISA Trans.*, vol. 91, pp. 41–51, Aug. 2019.

[16] J. Hui and J. Yuan, “RBF-based adaptive sliding mode controller with extended state observer for load following of nuclear power plant,” *Nucl. Eng. Des.*, vol. 360, Apr. 2020, Art. no. 110465.

[17] S. Han, H. Wang, and Y. Tian, “Model-free based adaptive nonsingular fast terminal sliding mode control with time-delay estimation for a 12 DOF multi-functional lower limb exoskeleton,” *Adv. Eng. Softw.*, vol. 119, pp. 38–47, May 2018.

[18] A. Mohammadi, M. Tavakoli, H. J. Marquez, and F. Hashemzadeh, “Nonlinear disturbance observer design for robotic manipulators,” *Control Eng. Pract.*, vol. 21, no. 3, pp. 53–67, 2013.

[19] S. Pashaei and M. Badamchizadeh, “A new fractional-order sliding mode controller via a nonlinear disturbance observer for a class of dynamical systems with mismatched disturbances,” *ISA Trans.*, vol. 63, no. 4, pp. 39–48, 2016.

[20] C. Jing, H. Xu, X. Song, and B. Lu, “Adaptive extended state observer-based flatness nonlinear output control for torque tracking of electro-hydraulic loading system,” *Trans. Inst. Meas. Control*, vol. 40, no. 10, pp. 2999–3009, Jun. 2018.

[21] A. Kuperman and Q.-C. Zhong, “Robust control of uncertain nonlinear systems with state delays based on an uncertainty and disturbance estimator,” *Int. J. Robust Nonlinear Control*, vol. 21, no. 1, pp. 79–92, Jan. 2011.

[22] M. Van, S. S. Ge, and H. Ren, “Finite time fault tolerant control for robot manipulators using time delay estimation and continuous nonsingular fast terminal sliding mode control,” *IEEE Trans. Cybern.*, vol. 47, no. 7, pp. 1681–1693, Jul. 2017.

[23] J. Lee, P. H. Chang, and M. Jin, “Adaptive integral sliding mode control with time-delay estimation for robot manipulators,” *IEEE Trans. Ind. Electron.*, vol. 64, no. 8, pp. 6796–6804, Aug. 2017.

[24] J. Baek, S. Cho, and S. Han, “Practical time-delay control with adaptive gains for trajectory tracking of robot manipulators,” *IEEE Trans. Ind. Electron.*, vol. 65, no. 7, pp. 5682–5692, Jul. 2018.

[25] Y. Zhu, J. Qiao, and L. Guo, “Adaptive sliding mode disturbance observer-based composite control with prescribed performance of space manipulators for target capturing,” *IEEE Trans. Ind. Electron.*, vol. 66, no. 3, pp. 1973–1983, Mar. 2019.

[26] P. Shi, F. Li, L. Wu, and C.-C. Lim, “Neural network-based passive filtering for delayed neutral-type semi-Markovian jump systems,” *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 28, no. 9, pp. 2101–2114, Sep. 2017.

[27] X. Li, F. Li, X. Zhang, C. Yang, and W. Gui, “Exponential stability analysis for delayed semi-Markovian recurrent neural networks: A homogeneous polynomial approach,” *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 12, pp. 6374–6384, Dec. 2018.

[28] Z.-H. Guan, G. Chen, and Y. Qiu, “On equillibria, stability, and instability of Hopfield neural networks,” *IEEE Trans. Neural Netw.*, vol. 11, no. 2, pp. 534–540, Mar. 2000.

[29] I. Poultanrangi, R. Shahnazi, and M. Sheikhan, “RBF neural network based PI pitch controller for a class of 5-MW wind turbines using particle swarm optimization algorithm,” *ISA Trans.*, vol. 51, no. 14, pp. 1–8, 2012.

[30] M. Sotgiuannos, A. Alexandridis, and H. Sarimveis, “Model predictive control for systems with fast dynamics using inverse neural models,” *ISA Trans.*, vol. 72, no. 6, pp. 61–77, 2018.

[31] S. Beyhan and M. Alci, “Stable modeling based control methods using a new RBF network,” *ISA Trans.*, vol. 49, no. 4, pp. 10–18, 2010.

[32] S. N. Huang, K. K. Tan, and T. H. Lee, “Adaptive motion control using neural network approximations,” *Automatica*, vol. 38, no. 2, pp. 27–33, 2002.

[33] D. Wang, Y. Zhao, X. Shao, Z. Zhang, and X. Zhao, “Neural network disturbance observer-based distributed finite-time formation tracking control for multiple unmanned helicopters,” *ISA Trans.*, vol. 73, pp. 208–226, Feb. 2018.

[34] Z. Zhang, “Structural optimization design of dynamic lower extremity exoskeleton system,” M.S. thesis, School Mech. Eng., Tianjin Univ. Sci. Technol., Tianjin, China, 2017.
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