PD Controller of a Lower Limb Exoskeleton Robot Based on Sliding Mode RBF Neural Network

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Abstract. The lower limb exoskeleton robot (LLER) is a human-robot interaction device that combines human functions and mechanical characteristics. Due to the complexity and strong coupling of human gait, it is difficult for LLER to be worn comfortably and safely for training. In such a scenario, the paper proposes a kind of proportional-derivative(PD) controller of LLER based on sliding mode RBF neural network(SMRBF-nn). In order to verify the effectiveness of the proposed control scheme, pertinent experiments were carried out. The gait data of the subject was collected through the motion capture system. A simulating model was established, different control methods, like conventional SMRBF-nn controller and PD controller based on SMRBF-nn, have been tested on the LLER. The experimental results show that the control strategy proposed in this paper can not only make LLER track the human body's gait trajectory, but also output appropriate torque when there is a disturbance.

Keywords: LLER · PD · SMRBF-nn · Human gait

1 Introduction

Since LLER has been developed, it has shown a genuine advantage in helping patients with lower limb dysfunction to assure rehabilitation training programs and physical movement assistance. In recent years, there have been more and more application scenarios of exoskeleton robots, and their performance has been continuously enhanced, especially assisting human movement and increasing the physical strength of the human muscle [1]. LLER controller plays an

The authors would like to thank the Henan Province Science and Technology R&D projects (182102410056, 202102210097, 202102210135), Young Backbone Teachers in Henan Province (2017GGJS117), and National Natural Science Foundation (62073297, U1813201) for their support of this work.

W. Fu et al. (Eds.): ICMTEL 2021, LNICST 387, pp. 427–436, 2021.
https://doi.org/10.1007/978-3-030-82562-1_40

important role in addressing the issue of Human-computer interaction, controller can quickly and accurately respond to human movement, and improves the fit between the robot and the human body [2]. The collection and analysis of data is the prerequisite to study the whole gait. In this paper, a set of motion capture system is used to collect the gait information of the human body during the movement process. The optical motion capture system is utilized to accurately locate the human gait trajectory in the experimental space [3]. Optical motion capture devices have been applied in many fields. Generally, the dynamic model is optimized on the basis of forward dynamics or reversing dynamics. Forward dynamics directly build muscle and joint models and obtain motion characteristics by optimizing motion equations [4]. In contrast, inverse kinematics regards the motion trajectory as the solution variable and calculates the joint torque according to the motion equation, which can avoid a mass of numerical integration [5]. However, humans' gait movement is extremely complicated, and the complex relationship between energy expenditure, muscle fatigue and joint load must be considered [6]. Therefore, there is no precise formula for the optimization of the dynamic model. Most of the optimization schemes are obtained from specific individuals and lack general adaptability. In order to reduce the error of the model and improve the accuracy of the gait, many researchers have proposed machine learning algorithms and got a good result [7]. For example, employed generalized regression neural network to predict the Fourier coefficient vector of a given gait parameter and lower limb anthropometric data, which is closer to the actual waveform than clinical gait analysis (CGA) data [8]. Radial basis function neural network (RBF-nn) is a nonlinear neural network with a simple structure, which can realize the kinematics controller and inverse dynamics controller, and has good control performance [9].

In this paper, using NoKov optical three-dimensional motion capture system, its gait capture accuracy meets our experimental requirements. This paper employs a control scheme that combines SMRBF-nn with PD to approximate human gait trajectory(as shown Fig. 1). In order to verify the effectiveness of the employed control scheme, we designed a gait capture experiment and MATLAB simulation for normal human. We also compared and evaluated the corresponding simulation results of the employed control scheme.

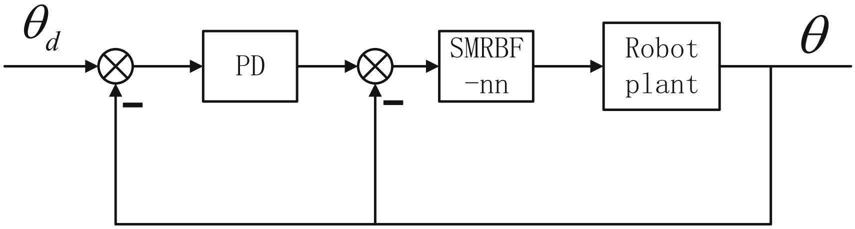

Fig. 1. System flow diagram

2 Laboratory Equipment

2.1 Motion Capture System

The current mainstream gait data acquisition equipment is based on the measurement method of high-speed optical cameras to capture the space trajectory of the markers. This paper uses NoKov optical motion capture system as shown in Fig. 2.

The subject's human joints are labeled with mark points, and the motion capture system will capture the gait trajectory of the subject walking in the experimental space. The captured gait data needs to be smoothed initially by the Cortex software, and then the human gait data is derived. Figure 3 depicts the relationships between joints angles.

2.2 Lower Limb Exoskeleton Robot

LLER realizes the combination of human control and mechanical power, so that humans have the advantages of mechanical power, speed and endurance and can better perform the functions of humans and machines. The LLER used in this paper adopts a flexible bionic design, has four active degrees of freedom and two passive degrees of freedom, and can be adjusted according to the wearer's body shape.

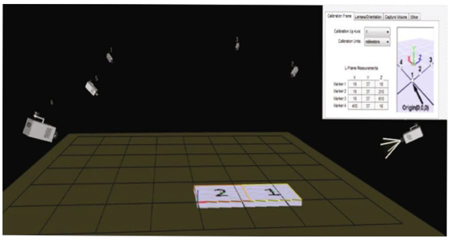

Fig. 2. NoKov optical motion capture system

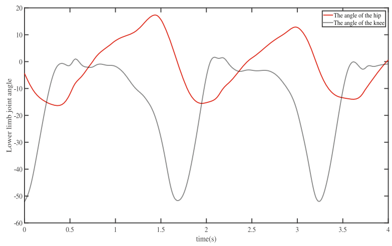

Fig. 3. Joints angle are processed by inverse kinematics

3 PD Controler Based on SMRBF-nn

3.1 Dynamic Modeling of LLER

Due to the symmetry of the gait motion, the dynamic model of the LLER can be simply used as a two-link model.

This paper uses a Lagrangian method to establish the exoskeleton dynamics model.

$$M(\theta)\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + G(\theta) = \tau - \tau_d \tag{1}$$

Where, $M(\theta) \in R^{2\times 2}$ is a positive definite inertia matrix, $C(\theta) \in R^{2\times 2}$ is the Coriolis force and centrifugal force matrix, $G(\theta) \in R^{2\times 1}$ is the gravity matrix, $\tau_d \in R^{2\times 1}$ is external disturbances, $\tau{=}[\tau_h, \tau_k]^T$ are the moments representing the hip joint and knee joint respectively. However, considering the force between the human body and the exoskeleton, the dynamic model expressed in (1) can be rewritten as follows:

$$(M{+}M_0)\ddot{\theta} + (C + C_0)\dot{\theta} + (G + G_0) = \tau - \tau_d \tag{2}$$

Where, M_0, C_0, G_0 are unknown.

Let's introduce a new variable such that: $x_1 = \theta$ and $x_2 = \dot{\theta}$. So, the dynamic model expressed in (2) can be rewritten as follows:

$$\begin{cases} \dot{x_1} &= x_2 \\ \dot{x_2} &= u(t) - f(t) - g(t) \end{cases} \tag{3}$$

So, $g(t) = M^{-1}C\dot{\theta} + M^{-1}G$, $f(t) = M^{-1}\tau_d + M^{-1}C_0\dot{\theta} + M^{-1}G_0 + M_0\ddot{\theta}$. It is difficult to obtain $f(t)$ due to the indetermination of the dynamic model of the LLER and unknown external disturbances effects. Before explaining the control methodology, the properties and the assumptions that are used in this paper are given as follows:

Property 1. Matrix M is symmetric and positive definite.

Property 2. There exist finite scalars $\eta_i > 0$, $i = 1, 2, 3, 4$. The $\|M\| \le \eta_1$, $\|C\| \le \eta_2$, $\|G\| \le \eta_3$ and $\|\tau_d\| \le \eta_4$ which means all items are bounded [10].

Property 3. The function $f(t)$ is bounded and globally Lipschitz function.

3.2 RBF Neural Network

The RBF neural network has three layers, namely the input layer, the hidden layer and the output layer.

Choose Gaussian function as the activation function of the RBF neural network, $H = [h_1, h_2, \cdots, h_j]^T$. The input of the neural network is x, the coordinate direction of the Gaussian function center point of the is c_j, and the width of the Gaussian function is b_j.

$$h_j = \exp(-\frac{\|x - c_j\|^2}{2b_j^2}) \tag{4}$$

The weight of the RBF neural network is $W = [w_1, w_2, \cdots, w_m]^T$. The output of the RBF neural network can be expressed as:

$$y_m = W^T H = w_1 h_1 + w_2 h_2 + \cdots + w_m h_m \tag{5}$$

The f contains all the information of the lower limb exoskeleton robot model. This article uses the RBF neural network to approximate f.

$$\widehat{f} = \widehat{W}^T h$$

The approximation error of the RBF neural network is:

$$\Delta f = f - \widehat{f} = \widetilde{W}^T h + \varepsilon \tag{6}$$

Where, ε is a small positive number, $\widetilde{W} = W - \widehat{W}$, $\|W\|_F \leq W_{\max}$.

The input of the RBF neural network is $x = [e, \dot{e}, \theta_d, \dot{\theta}_d, \ddot{\theta}_d]^T$.

3.3 Controller Design

Define tracking error $e = x_d - x_1$. Where, $x_d = [\theta_{dh}, \theta_{dk}]^T$ is the desired joint angle of the robot's hip joint and knee joint.

Close the loop via the PD controller, which is designed as follow:

$$u = \ddot{\theta}_d + f + g + \tau_{PD} \tag{7}$$

Where, $\tau_{PD} = K_P e + K_D \dot{e}$.

Combining Eq. (2) and (7), we can obtain the following equation:

$$\ddot{e} + \tau_{PD} = 0 \tag{8}$$

It is obvious that the poorly known parameters and external disturbances of the plant f is eliminated. The tracking error can be close to zero through a simple zero-pole assignment.

Thus, the PD controller based on SMRBF-nn utilized can be designed as:

$$u = \ddot{\theta}_d + \widehat{f} + g + \tau_{PD} \tag{9}$$

Combining Eq. (2) and (9), we can obtain the approximation error of the RBF neural network following equation:

$$\Delta f = f - \hat{f} = \ddot{e} + \tau_{PD} \tag{10}$$

Combining formula (8), we can find that the tracking error may not converge to zero. But the tracking error can be limited in a relatively small bound, namely $|\Delta f| \leq F$ with F a constant positive value.

The τ_{SRRBF} is added to the PD controller based on SMRBF-nn to compensate for the estimation error Δf. Then, the PD controller based on SMRBF-nn is defined as follow:

$$u = \ddot{\theta}_d + \hat{f} + g + \tau_{PD} + \tau_{SMRBF} \tag{11}$$

From Eq. (2), the following closed loop equation can be obtained as:

$$\Delta f = f - \hat{f} = \ddot{e} + \tau_{PD} + \tau_{SMRBF} \tag{12}$$

The sliding mode function is designed as:

$$r = \dot{e} + \lambda e \tag{13}$$

After reaching the sliding mode surface, the tracking error e will gradually approach zero. Its derivative can be calculated as follow:

$$\dot{r} = \ddot{e} + \lambda\dot{e} = \lambda\dot{e} - \tau_{PD} - \tau_{SMRBF} + \Delta f \tag{14}$$

The τ_{SRRBF} can be designed as:

$$\tau_{SRRBF} = \lambda\dot{e} - \tau_{PD} + \eta\ sgn(r) \tag{15}$$

Where, $\eta > 0$. So,

$$\dot{r} = -\eta\ sgn(r) + \Delta f \tag{16}$$

Finally, the design control law becomes:

$$u = \ddot{\theta}_d + \hat{f} + g + \lambda\dot{e} + K_v r - v + \eta\ sgn(r) \tag{17}$$

Where, K_v is a positive definite matrix, $u(t) = M^{-1}\tau$.
The adaptive law of RBF neural network is:

$$\widehat{W} = \gamma h r^T \tag{18}$$

Where, $v = -(\varepsilon + b_d)sgn(r)$ is robust, $\gamma = \gamma^T > 0$, b_d is a positive number.
The Lyapunov function is:

$$V = \frac{1}{2}r^2 + \frac{1}{2}\widetilde{W}^T\gamma^{-1}\widetilde{W} > 0 \tag{19}$$

Its derivative can be expressed as:

$$\dot{V} = r\dot{r} + \widetilde{W}\gamma^{-1}\dot{\widetilde{W}} = \Delta f r - K_v r^2 - \eta\,|r| + vr + \widetilde{W}\gamma^{-1}\dot{\widetilde{W}} \tag{20}$$

Where,

$$\dot{\widetilde{W}} = -\dot{\widehat{W}} = -\gamma h r^T$$

$$\Delta f r + vr + \widetilde{W}\gamma^{-1}\dot{\widetilde{W}} = -b_d\,|r|$$

So,

$$\dot{V} = -K_v r^2 - (\eta + b_d)\,|r| \leq 0 \tag{21}$$

When $\dot{V} \equiv 0$, the $r = 0$, according to the principle of LaSalle invariance, the entire control system is progressively stable.

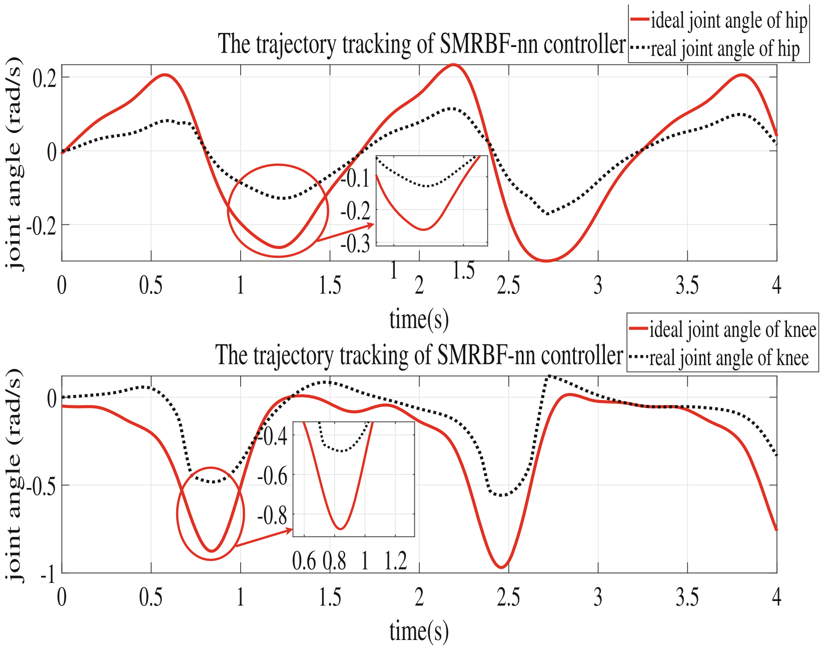

Fig. 4. The joint trajectory tracking state when using the SMRBF neural network controller

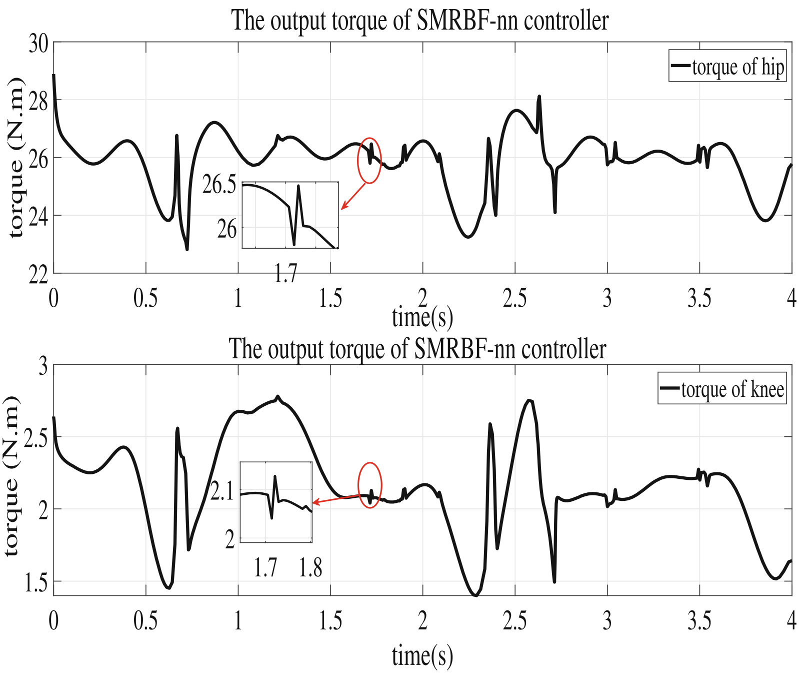

Fig. 5. The joint torque state when using the SMRBF neural network controller

4 Simulation

In order to verify the feasibility of the algorithm, the gait data of a male subject (height 170 cm, weight 66.51 kg) was selected as the reference trajectory. Assuming that the mass of the LLER is evenly distributed, and the initial state is $\theta_0 = [0, 0]^T$. In the design of the controller, the desired joint angles of the hip and knee joints are obtained from the human gait trajectory by the motion capture system.

Designed parameters in the controller is determined as:

$b_d = 10$, $\gamma = diag(15, 15)$, $\lambda = diag(20, 20)$, $K_v = diag(30, 30)$, $K_P = [50, 50]^T$, $K_D = [0.2, 0.2]^T$, $c = \begin{bmatrix} -1 & -0.9 & -0.7 & -0.3 & 0 & 0.2 & 0.5 & 1 & 1.2 \\ -1 & -0.9 & -0.7 & -0.3 & 0 & 0.2 & 0.5 & 1 & 1.2 \end{bmatrix}$.

In order to highlight a better contrast, in the simulation experiments, we will use the conventional RBF neural network controller and PD controller based on SMRBF-nn. The simulation results are shown in the Fig. 4 and 5, and the Fig. 6 and 7, respectively.

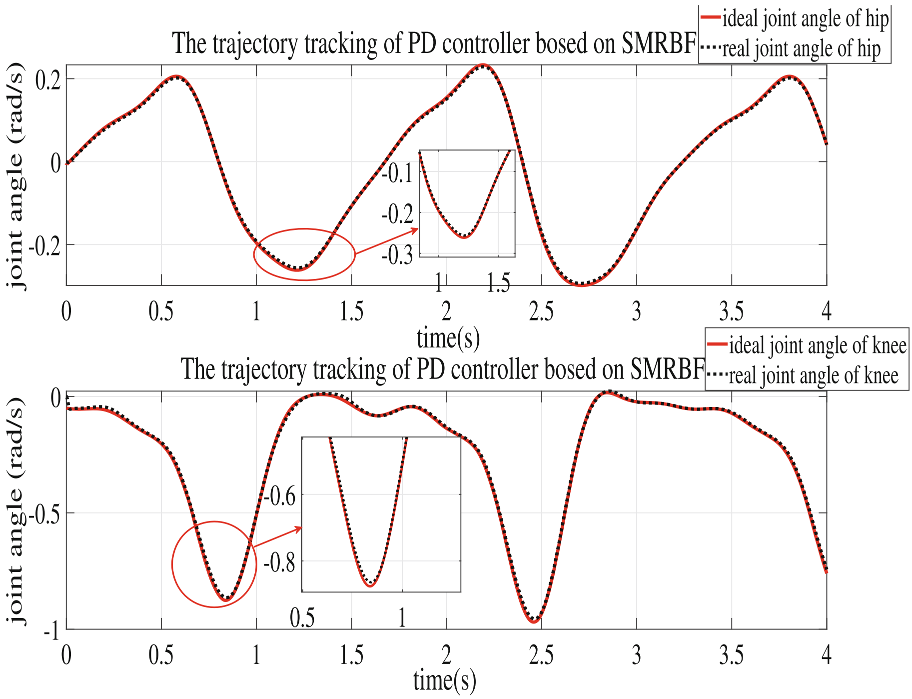

Fig. 6. The joint trajectory tracking state when using the PD controller based on SMRBF-nn

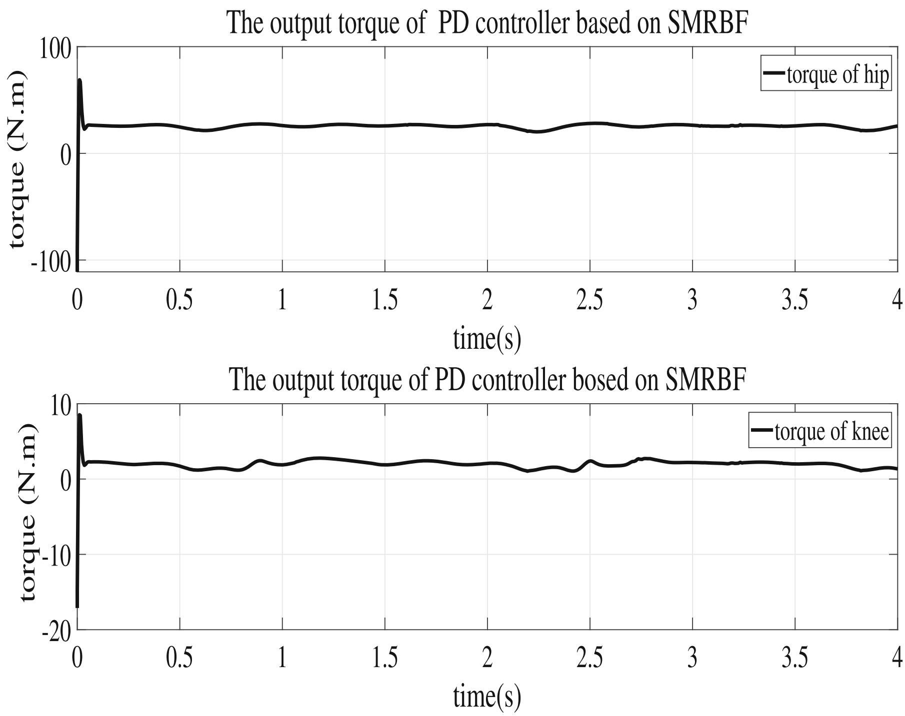

Fig. 7. The joint torque state when using the PD controller based on SMRBF-nn

Experimental results show the tracking of joint angle, tracking error of joint, and the controller output torque. Figure 4 and 6 show the joint trajectory performance for the joint angle of the hip and knee. As could be seen from Fig. 6, the accuracy between ideal joint and the real joint is less than 0.01rad/s. But the accuracy is more than 0.4rad/s for the Fig. 4. It can be seen from the simulation results that the joint angle of the LLER can track the collected normal humans' gait trajectory well, and the tracking error can quickly converge to zero, when employing PD controller based on SMRBF-nn. Furthermore, the conventional SMRBF-nn controler has high-frequency chatter from the Fig. 5. However, the Fig. 7 shows that the output torque is smoother and more in line with the characteristics of human motion. Taking into account that, if the practical application, the PD controller based on SMRBF-nn will be better than just utilize the SMRBF-nn controller.

5 Conclusion

The motion characteristics of LLER are analyzed, and normal human gait data is collected by the motion capture system in this paper. The most important thing is that this paper proposes a PD controller based on the SMRBF-nn. And the controller allows the LLER to follow the normal human gait for rehabilitation training, while ensuring the smooth and supple output torque.

It is verified by MATLAB simulation that the output joint angle of the LLER can quickly track the desired joint angle. Compared with the traditional SMRBF-nn, the control strategy proposed in this paper has smaller joint angle errors, the output torque is smaller and more compliant.

The research also has some shortcomings to be improved. Firstly, only two subjects participated in the experiment, and the results obtained are less generalized. Secondly, LLER cannot change control strategy based on human movement intention. We will recruit more subjects for data collection and introduce EEG and EMG signals to predict human gait in the future.

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