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Design of Front Feed PID Control System for the Limb Rehabilitation Robot based on BP Neural Network

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***Abstract* - Lower limb rehabilitation robot can provide rehabilitation training therapy for patients with lower limb hemiplegia and poor flexibility caused by stroke or accident.Realizing the precise control of rehabilitation robot can improve the effect of rehabilitation training.The control system is one of the key modules of the lower limb rehabilitation robot, and its performance will have a direct impact on the effect of rehabilitation training.Artificial neural network has the ability of self-learning and self-adaptation.Front feed control has the ability to improve the steady-state accuracy and response speed of the system.The integrated application of neural network and front feed control in the control system can optimize and improve the response speed, accuracy and follow-through of the overall control system.Therefore, the intelligence of control system of lower limb rehabilitation robot device is improved and the effectiveness of rehabilitation training is improved.This paper proposes a front feed PID control system based on neural network.Through step signal and gait tracking simulation experiments, the tracking effects of traditional PID, neural network PID and neural network front feed PID are compared.According to the simulation experiment, the neural network front feed PID can effectively improve the response speed and tracking effect of the system.**

Index Terms - Lower limb rehabilitation robot, BP Neural Networks, Front feed control ,PID control.

I. INTRODUCTION

Stroke is a vascular disease caused by the death of brain cells due to hypoxia. According to statistics, about 15 million people in the world suffer from stroke every year, of which 5 million die from stroke and 5 million permanently maim. After reaching 65 years of age and suffering from stroke ,30% of patients need auxiliary walking and 26% need help [1] in self-care. Stroke is the main cause of human disability in many countries. The motor disorder induced by stroke disease has seriously reduced the quality of life of patients [2].Researchers around the world are seeking a scientific and effective rehabilitation model for stroke patients.Since then rehabilitation robot has emerged.

Rehabilitation robots cover a wide range of disciplines. Including machinery, electronics, control, rehabilitation medicine.The goal is to develop a robot that simplifies the traditional artificial treatment process.Take the pressure off doctors.Rehabilitation robot has its unique advantages in repeatability, stability and accuracy.Therefore, scientific training plans can be provided for patients to improve training efficiency.Thus, the problem of lack of accuracy and quantification of artificial assisted rehabilitation movement is solved[3]-[4].

Most rehabilitation equipment has the function of passive training and active training. Combined with human kinematics.The corresponding motor drive mechanical device is controlled to simulate the motion track of each joint. Passive motion is suitable for the early rehabilitation of hemiplegic patients. The equipment drives the motion of each joint and the joints follow. The stability of the control system is high. It is necessary to ensure that the rehabilitation machine is stable and reliable during the auxiliary exercise. Avoid secondary injury to patients. Passive training is the only way for the rehabilitation of most patients with dyskinesia. Good passive training is helpful to maintain the joint patients and avoid further muscle atrophy.

Nowadays, PID control is often used to realize passive control of rehabilitation equipment. For example, Huang etal of Huazhong University of Science and Technology use PID control to complete passive motion test on new wearable upper limb rehabilitation equipment. zhang etal use pd control method to realize continuous passive motion (cpm)[5]. However, the traditional control methods have the problems of poor tracking effect, difficult tuning of controller parameters and unstable system after model mismatch[6].

To solve the above problems, this paper proposes a front feed PID control system for lower limb rehabilitation robot based on BP neural network. Whether it is traditional PID control or neural network based PID control, most of them are feedback control. For the system with fast change of input signal, its follow error is large. front feed control can effectively improve the dynamic response ability of the system by introducing control quantity. The neural network has the ability of arbitrary nonlinear expression, and can realize the front feed PID control with the best combination by learning the system performance. Using the BP neural network, the front feed PID controller with parameters ***kp,ki,kd,ks*** self-tuning can be established.

The following is the structure of this paper. The Section II introduces the acquisition of standard gait data, including standard gait terms, and standard gait functions. The Section III introduces the controller design. including traditional PID system, neural network PID system, neural network front feed PID system.Section IV is the experiment and the result. Section V is the conclusion.

II. STANDARD GAIT ANALYSIS AND ACQUISITION

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A. Gait cycle analysis

Gait is the ultimate goal of the central nervous system at the biomechanical level. Gait depends on the coordination of the central nervous system, peripheral nervous system and musculoskeletal system. When the normal physiological function of our lower extremity muscles, ligaments, bones, joints and even the brain, spinal cord, peripheral nerves and coordination and balance are damaged, it can lead to different degrees of walking difficulty and show abnormal gait. So it's important to get the standard gait

A gait cycle is the time experienced from one foot to the ground again. gait cycle can be divided into single leg support phase, double leg support phase and swing phase. The supporting phase refers to the process of supporting the weight of the human body, that is, the time when the foot is in contact with the ground to leave, and the swing phase refers to the process of the foot staying in space during walking. As shown in Fig .1, if only the right limb is considered, the first 62% is the supporting phase and the latter 38% is the swing phase.

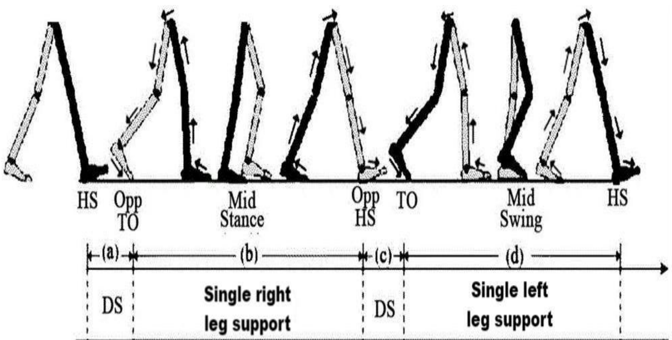

Fig. 1 Gait cycle

B. Standard gait acquisition

The basic function of the lower limb rehabilitation robot is to help the patient return to normal walking ability, so in rehabilitation In the process, it is necessary to make the patients carry out rehabilitation training to simulate normal gait, so as to stimulate the corresponding neurons, make them form neural memory and speed up the rehabilitation process.

Opensim is a software developed by stanford university for human motion simulation.Because of its simplicity and practicability, opensim is widely used in many fields, such as rehabilitation medicine,neurology, bone medicine, ergonomics and so on.Opensim the human body model interface is shown in Fig.2.The bone muscle model has been integrated in the software.The gait of normal people and hemiplegic patients has been studied.The bone muscle model can be directly called in the process of motion simulation, and the user is not required to build the model. Easy to use.Open the software, load the normal human model, select the normal gait.And get the motion track of the knee and hip joints of the left leg and the right leg during the same period of normal walking as shown in Fig.3.The hip flexion represents the flexion and extension angle of the hip joint and knee angle the flexion and extension angle of the knee joint.

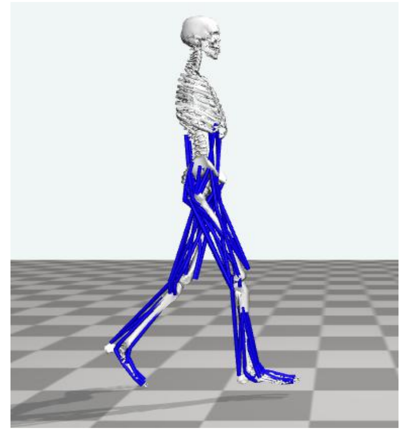

Fig. 2 Human body simulation model

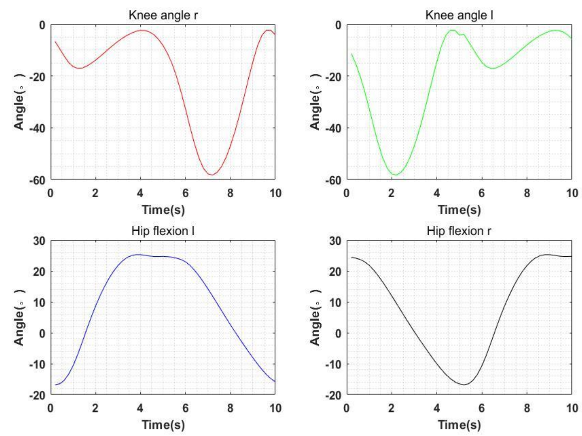

Fig. 3 Standard gait curve

Load the motion file normal_gait in the software by referring to the measured human gait data.The mannequin will perform normal gait movements according to the system Settings, thus obtaining a standard gait curve.The data of a completed gait cycle was exported into Excel format, and the obtained standard gait data was imported into Matlab and fitted through Fourier6 in the Cftool toolbox.The fitting effect is shown in Fig.4, Fig.5,Fig.6 and Fig.7.

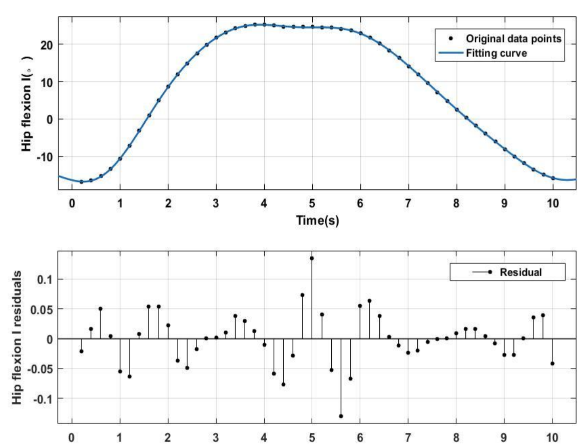

Fig. 4 Left hip fitting curve

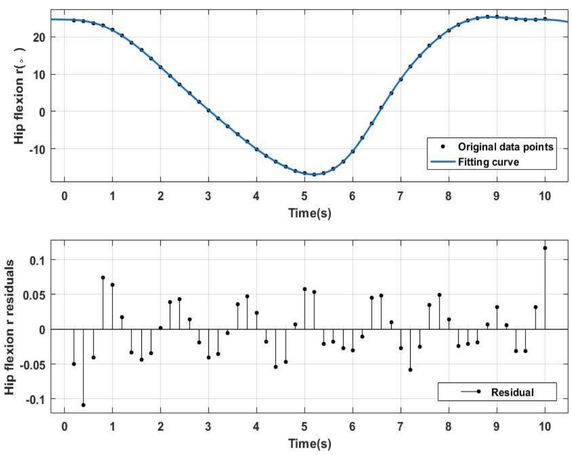

Fig. 5 Right hip fitting curve

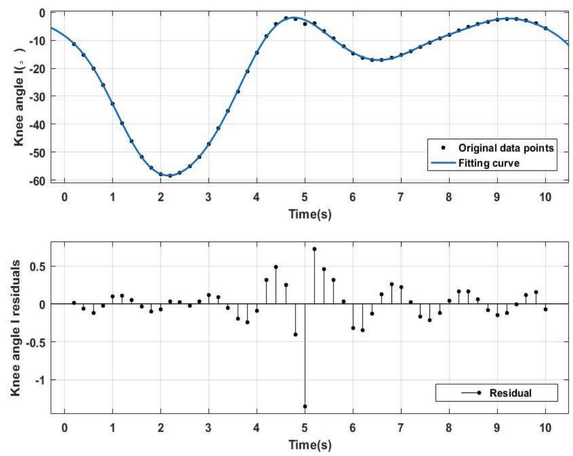

Fig. 6 Left knee fitting curve

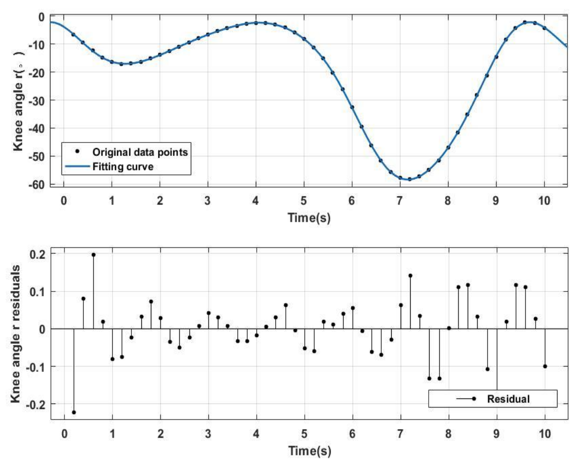

Fig. 7 Right knee fitting curve

The motion angle curves of each joint obtained by curve fitting are Equation 1, in which the parameters are shown in Table I.

$$\begin{aligned} f(x) &= a0 + a1\cos(x\omega) + b1\sin(x\omega) + a2\cos(2x\omega) + b2\sin(2x\omega) \\ &+ a3\cos(3x\omega) + b3\sin(3x\omega) + a4\cos(4x\omega) + b4\sin(4x\omega) \\ &+ a5\cos(5x\omega) + \mathrm{b5}\sin(5x\omega) + a6\sin(6x\omega) + \mathrm{b6}\sin(6x\omega) \end{aligned} \tag{1}$$

TABLE I

GAIT EQUATION PARAMETERS

Equation parameter	Left hip joint	Right hip joint	Right knee joint	Left knee joint
a0	8.152	7.614	-20.34	-19.95
a1	-20.66	20.76	1.635	-2.633
b1	3.433	-3.514	19.43	-18.86
a2	-4.044	-3.589	13.9	13.8
b2	-0.8567	-1.094	-8.082	-9.092
a3	-0.0656	0.0144	0.09082	0.5033
b3	-1.64	1.547	-4.514	4.477
a4	-0.1577	-0.09597	0.72	0.4756
b4	-0.2008	-0.1422	-0.5059	-0.2062
a5	0.1545	-0.1952	0.371	-0.1264
b5	-0.2022	0.1846	-0.8219	0.6228
a6	0.09905	0.09202	-0.2266	-0.373
b6	0.00698	0.05049	-0.1739	0.1302
w	6.193	6.311	6.294	6.14

III. BP NEURAL NETWORK FRONT FEED PID CONTROLLER DESIGN

A. Front Feed PID Controller

The front feed PID controller block diagram is shown in Fig.8, where the input of the PID controller is system input r(t), system output y(t) and error signal e(t). The input of the front feed controller is system input r(t). Output of the controller is the weighted sum of the output of the PID controller and the front feed controller.

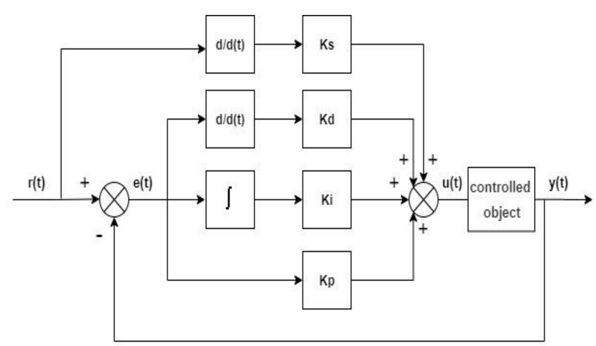

Fig. 8 Front feed PID controller principle

Front feed PID controller time domain is Equation 2 :

$$u(t) = K_p e(t) + K_i \int e(t) d(t) + K_d \frac{de(t)}{dt} + K_s \frac{dr(t)}{dt} \tag{2}$$

Where e(t) is the error signal, ***kp,ki,kd,ks*** are the proportional coefficient, integral coefficient, differential coefficient and front feed coefficient, respectively, and u (t) is the control output.

The time-domain equation is discretized to obtain the positional PID discrete equation and the incremental PID discrete equation, which are Equation 3 and Equation 4 respectively.In this paper,the position type PID is used.

$$u(k) = K_p e(k) + K_i \sum_{j=0}^{k} e(j) + K_d(e(k) - e(k-1)) + K_s(r(k) - r(k-1)) \tag{3}$$

$$\begin{aligned} u(k) &= K_p(e(k) - e(k-1)) + K_i e(k) + K_d(e(k) - 2e(k-1) \\ &+ e(k-2)) + K_s(r(k) - 2r(k-1) + r(k-2)) \end{aligned} \tag{4}$$

B. BP neural network front feed PID controller

BP neural network is a front feed network trained by error back propagation algorithm. It is often widely used because of its simple structure, self-learning, adaptive and ability to deal with nonlinear problems[7]. With the above advantages of neural network, a front feed PID control based on neural network is proposed by combining it with front feed PID control. The controller can adjust the four parameters of front feed PID by neural network, which can solve the problem that the parameters of traditional PID are difficult to set and the setting effect is poor. The basic structure of the controller is shown in Fig.9. The controller is mainly composed of two parts, BP neural network and front feed PID, the former self-tuning the front feed PID parameters through self-learning ability, and the latter directly controls the control object in the form of front feed and feedback.

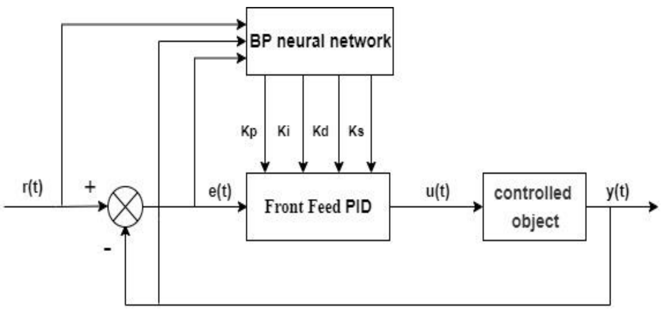

Fig. 9 Neural network front feed PID controller principle

BP basic structure of the neural network is shown in Fig .10, It is mainly composed of input layer, hidden layer and output layer, research shows that,the three-layer BP neural network can accurately approximate the continuous nonlinear function [8]-[11]. So here we use a three-layer neural network to approximate the function.The input layer is three nodes, r(t), error signal e(t) and output signal y(t).The hidden layer uses five hidden nodes.The output layer uses four nodes, ***kp,ki,kd,ks,*** of four parameters corresponding to front feed PID respectively.

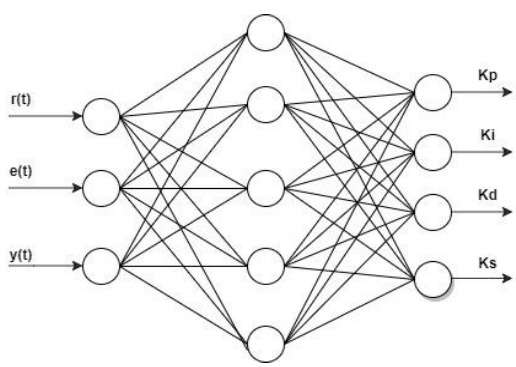

Fig. 10 BP Neural Network Structure

The output of the input layer node is Equation 5:

$$O_{\mathrm{j}}^{(1)} = x_j \qquad (j = 1,2,3) \tag{5}$$

The input of the hidden layer node is Equation 6:

$$net_{\mathrm{i}}^{(2)}(k) = \sum_{j=1}^{3} w_{ij}^{(2)} O_j^{(1)} \qquad (i = 1,2,.....,5) \tag{6}$$

The output of the hidden layer node is Equation 7:

$$O_{\mathrm{i}}^{(2)}(k) = f(net_i^{(2)}(k)) \tag{7}$$

Among them, the activation function of hidden layer node is sigmoid function, the expression is Equation 8:

$$f(x) = \tan h(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{8}$$

The input of the output layer node is Equation 9:

$$net_n^{(3)}(k) = \sum_{n=1}^{4} w_{ni}^{(3)} O_i^{(2)}(k) \qquad (n = 1,2,3,4) \tag{9}$$

The output of the output layer node is Equation 10:

$$O_{\mathrm{n}}^{(3)}(k) = f(net_n^{(3)}(k)) \tag{10}$$

Since the parameters set by front feed PID can not be negative, the activation function selects the non-negative sigmoid function to ensure that the output of the parameters is positive, and its expression is Equation 11:

$$f(x) = \frac{1}{2}(1 + \tan h(x)) = \frac{e^x}{e^x + e^{-x}} \tag{11}$$

The cost function is defined is Equation 12:

$$E(k) = \frac{1}{2}(r(k) - y(k))^2 \tag{12}$$

According to the gradient descent method, the weights are obtained as follows Equation 13:

$$\Delta w_{ni}^{(3)}(k) = -\eta \frac{\partial E(k)}{\partial w_{ni}^{(3)}} + \alpha w_{ni}^{(3)}(k-1) \tag{13}$$

Among them, η the learning rate is α the inertia coefficient, and the cost function is Equation 14:

$$\frac{\partial E(k)}{\partial w_{ni}^{(3)}} = \frac{\partial E(k)}{\partial y(k)} \frac{\partial y(k)}{\partial u(k)} \frac{\partial u(k)}{\partial O_n^{(3)}(k)} \frac{\partial O_n^{(3)}(k)}{\partial net_n^{(3)}(k)} \frac{\partial net_n^{(3)}(k)}{\partial w_{ni}^{(3)}} \tag{14}$$

Since the following variables are unknown, y(k),u(k) and their relative changes can be obtained, as shown in Equation 15:

$$\frac{\partial y(k)}{\partial u(k)} = \frac{y(k) - y(k-1)}{u(k) - u(k-1)} \tag{15}$$

The output layer is defined Equation 16:

$$\begin{cases} K_{\mathrm{p}} = O_1^{(3)}(k) \\ K_{\mathrm{i}} = O_2^{(3)}(k) \\ K_{\mathrm{d}} = O_3^{(3)}(k) \\ K_{\mathrm{s}} = O_4^{(3)}(k) \end{cases} \tag{16}$$

Equation 16 is brought into Equation 3, and the output of the controller is obtained is Equation17,find the derivative Equation 18:

$$u(k) = O_1^{(3)}(k)e(k) + O_2^{(3)}(k)\sum_{j=0}^{k} e(k) \\ O_3^{(3)}(k)(e(k) - e(k-1)) + O_4^{(3)}(k)(r(k) - r(k-1)) \tag{17}$$

$$\begin{cases} \dfrac{\partial u(k)}{O_1^{(3)}} = e(k) \\ \dfrac{\partial u(k)}{O_2^{(3)}} = \sum_{j=0}^{k} e(k) \\ \dfrac{\partial u(k)}{O_3^{(3)}} = e(k) - e(k-1) \\ \dfrac{\partial u(k)}{O_4^{(3)}} = r(k) - r(k-1) \end{cases} \tag{18}$$

The output layer weight adjustment Equation 19 is obtained by bringing Equation15,18 into Equation13:

$$\Delta w_{ni}^{(3)} = -\eta \beta_n^{(3)} O_i^{(2)}(k) + \alpha w_{ni}^{(3)}(k-1) \tag{19}$$

Above $\beta_n^{(3)}$ is Equation 20 :

$$\beta_n^{(3)} = e(k)\operatorname{sgn}\left(\frac{y(k)-y(k-1)}{u(k)-u(k-1)}\right)\frac{\partial u(k)}{\partial O_n^{(3)}(k)} f'(net_n^{(3)}(k)) \tag{20}$$

In the same way, the weight adjustment of the hidden layer is Equation 21:

$$\Delta w_{ij}^{(2)} = -\eta \sum_{n=1}^{4} \beta_n^{(3)} w_{ni}^{(3)} f'(net_i^{(2)}(k)) O_j^{(1)}(k) + \alpha w_{ij}^{(2)}(k-1) \tag{21}$$

IV.SIMULATION AND RESULTS

In the early stage, the dynamic modeling and analysis of the lower limb rehabilitation robot were carried out, and the dynamic equation was established, which laid a theoretical foundation for the design and simulation of the controller in this section. This section only carries on the control simulation to the rehabilitation robot left hip joint, the right hip joint, the rehabilitation robot concrete structure is shown in Fig .11.

The simulation of the controller in this paper is established by simulink combined with the s-function model, as shown in Fig.12. The step signal and the standard gait trajectory signal are input into the neural network front feed PID controller.The parameters are adjusted online.The corresponding control signals are output. The sampling frequency is 0.1s.The learning rate is 0.1.The inertia coefficient is 0.05.The initial weights of the neural network are generated randomly.The simulation time is 10s.The simulation step is 0.01.

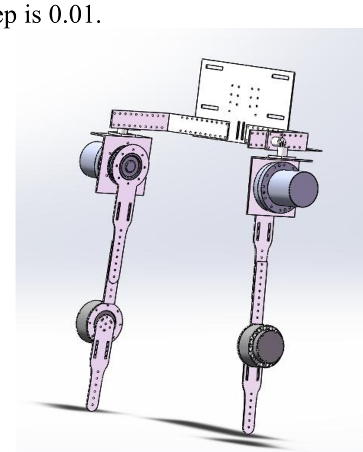

Fig. 11 Lower limb rehabilitation robot structure

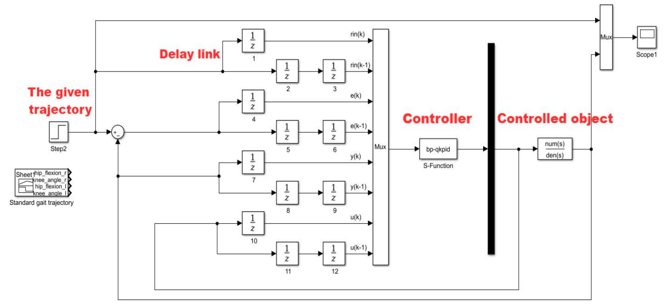

Fig. 12 Simulation PID BP Neural Network front feed

Because the initial value of the input of the s function is uncertain, it can only be determined after several iterations. If the default setting is 0, it will lead to the case of dividing by 0 in the iteration process. Cause an error. So add the delay module after the input signal.

The response curve PID,BP step signal and the response curve of standard gait signal are obtained by simulation analysis of traditional PID and BP neural network front feed control algorithm. The step signal response and error contrast diagram are shown in Fig .13 and Fig .14.

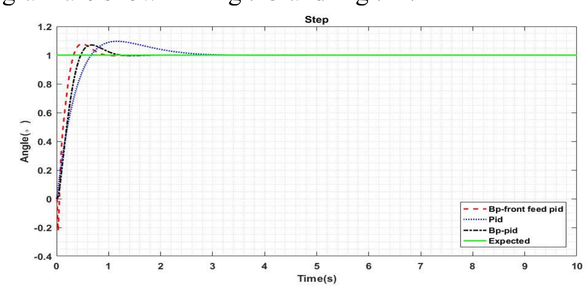

Fig. 13 step response

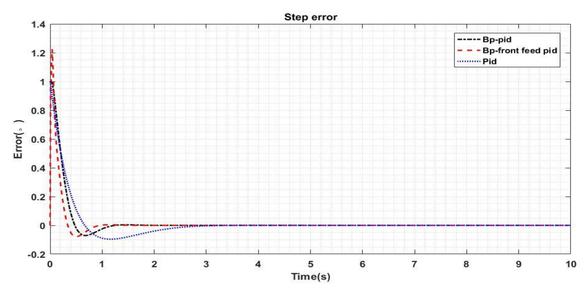

Fig. 14 Step response error

The simulation contrast figure, found that the maximum overshoot is about 10%, traditional PID adjustment time is about 3s, poor response speed.And the neural network PID overshoot and response speed are improved, but there are still certain hysteresis, adjust time about 0.7s.The neural network front feed PID under the effect of the above, overshoot volume drop is about 7%,the adjustment time is about 0.5s,The response speed is improved again, and the better control effect is achieved.

Secondly, the trajectory tracking and error analysis of the three kinds of controllers are carried out respectively. The track and error of the right leg hip joint are shown in Fig.15 and Fig.16, and the track and error of the left leg hip joint are shown in Fig.17 and Fig.18.

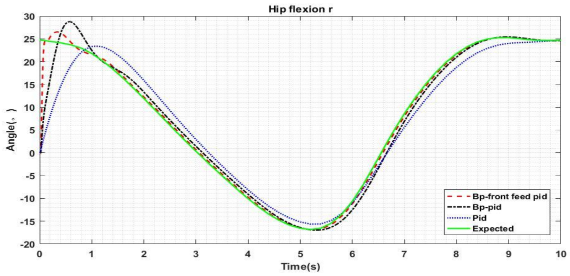

Fig. 15 Track of hip in right leg

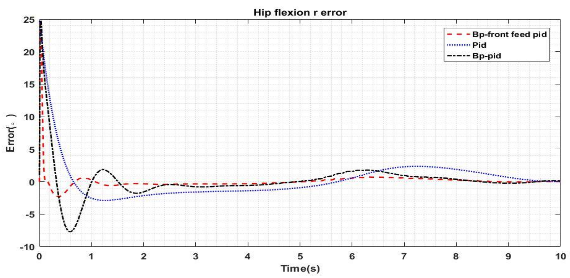

Fig. 16 Right leg hip tracking error

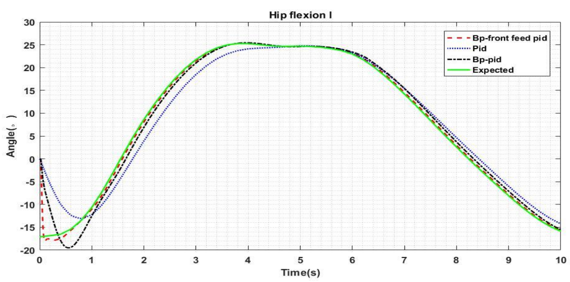

Fig. 17 Track of hip in left leg

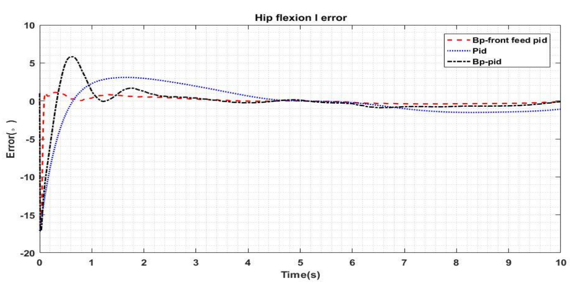

Fig. 18 Left leg hip tracking error

The simulation results show that the BP neural network front feed PID has the smallest overshoot, the fastest response speed, the good tracking effect and the error approaching to 0, which can complete the gait tracking task well.

V. CONCLUSION

To improve the tracking accuracy of rehabilitation personnel in passive training.A front feed PID control strategy for lower limb rehabilitation robot based on BP neural network was proposed.The problem of large tracking error and slow response speed is solved.Through the comparison with the traditional PID and neural network PID simulation.The tracking error of the control strategy is obviously reduced, which can show good control performance and greatly improve the tracking accuracy of rehabilitation personnel training.Therefore, the BP neural network front feed PID can be better applied to the passive tracking training of lower limb rehabilitation robot.In the future research, we will optimize the control strategy through genetic algorithm, particle swarm optimization and other methods, so as to further improve the tracking accuracy and response speed.

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