Analysis of PID Control and Impedance Control Based on Upper Limb Rehabilitation Training Robot

Junjun Cong *

College of Electromechanical Engineering, China University of Mining and Technology, Xuzhou, Jiangsu, 221000, China

* Corresponding Author Email: 03223990@cumt.edu.cn

Abstract. In the process of upper limb rehabilitation training robots assisting patients in the training of the affected limbs, a stable and sensitive control system is a prerequisite to ensure efficient training results. On the basis of traditional proportional-integral-derivative (PID) control and impedance control, this paper aims to explore the current status of the application of fuzzy PID, neural network and human-computer interaction in robotic rehabilitation training, and analyze the current research with examples. Finally, this paper proposes a method that integrates human-computer interaction, fuzzy PID, neural network and deep learning. The method uses sensors to analyze the neuroelectrical signals, human-computer interaction forces, and language systems, respectively and uses FNN controllers for control and reinforcement learning. The method can provide a more stable, efficient and personalized rehabilitation training system for upper limb rehabilitation training robots. The optimization method proposed in this paper is helpful for the subsequent improvement of the upper limb rehabilitation training robot. However, the method proposed in this paper has the limitation that it is difficult to optimize the superposition of specific functions.

Keywords: PID control, impedance control, human-robot interaction, upper limb rehabilitation.

1. Introduction

With the increase in the aging population, age-related strokes have increased, and usually, the upper limbs of hemiplegic patients are more severely affected than the lower limbs. Clinical experiments have shown that timely and appropriate rehabilitation training can help stroke patients recover their damaged limb motor functions. Therefore, the upper limb rehabilitation training robot is getting more and more attention as an auxiliary tool. It not only improves the efficiency of rehabilitation training but also ensures the safety and patient participation in the training process, thus providing better rehabilitation results for stroke patients.

Currently, upper limb rehabilitation training control mainly uses two methods, proportional-integral-derivative (PID) control and impedance control. Chen Guiliang's team added a PID controller to the control system in order to achieve the requirements of fast response speed and high stability [1]. Yang Dayong et al. utilized the theory of robot impedance control in order to construct a robotic arm control method that expects interactive force tracking [2]. Hai-Fang Mu's team combined PID control and impedance control to achieve better control performance [3]. However, both methods still have limitations. First, PID control is less adaptable to nonlinear and time-varying systems, making it difficult to achieve the best control effect; second, impedance control is highly dependent on the accuracy of the robotic arm dynamics model and is complicated to implement. Not only that, both of them may have stability problems, and it is difficult to adapt to complex nonlinear systems and individual differences, so both of them need to be further optimized. By optimizing control methods and enhancing human-computer interaction, the safety and effectiveness of rehabilitation training can be improved, the risk of secondary injuries to patients can be reduced, and patient engagement can be enhanced. In addition, these studies can help realize personalized rehabilitation treatment plans and promote technological progress in the field of rehabilitation.

The purpose of this paper is to summarize the current research status of upper limb rehabilitation training robots. First, this paper will illustrate the shortcomings of traditional PID control and impedance control. Secondly, this paper discusses the optimization control method from three perspectives: fuzzy PID, neural network and human-machine interaction. Finally, an integrated optimal control method is proposed to improve the effect of upper limb rehabilitation training.

2. Traditional methods

2.1. PID control

PID control is an automatic control method, through the proportional (P), integral (I), and differential (D) three links to adjust the control amount to reduce the system error. The proportional link responds quickly to deviations, the integral link eliminates steady-state errors, the differential link predicts deviation trends and the combination of the three improves system stability and response speed.

The output of the PID controller can be calculated by the following equation:

$$u(t)=K_P e(t) + K_i \int_0^t e(\tau) d_\tau + K_d \frac{de(t)}{dt} \tag{1}$$

Where u(t) is the output of the controller at time t. e(t) is the deviation at time t, i.e., the difference between the desired value and the actual value. Kp, Ki, Ka are the proportional, integral, and differential gains, respectively.

2.2. Impedance Controls

Impedance control is a robot control technique that controls the robot's interaction with the environment by simulating a rigid connection on the robot's end-effector, allowing the robot to better adapt to changes in the environment while performing tasks.

Basic Equations of Impedance Control.

The core equation of impedance control can be expressed as:

$$M_d \ddot{\tilde{x}} + D_d \dot{\tilde{x}} + K_d x = F_{ext} \tag{2}$$

Where:$\cdot M_d$is the mass matrix of the target impedance model.$\cdot D_d$ is the damping matrix of the target impedance model.$\cdot K_d$ is the stiffness matrix of the target impedance model.$\cdot \tilde{x}$ is the positional deviation, defined as:$\tilde{x}=x_d$-x,the difference between the desired position and the actual position x.$\cdot F_{ext}$the external force.

3. Optimization methods

3.1. Fuzzy PID

Although the traditional PID algorithm is simple and easy to use, its invariant parameters are difficult to use in complex nonlinear systems. Fuzzy PID is a control strategy that combines the traditional PID control with fuzzy logic, which is able to adaptively adjust the PID parameters according to the system error and real-time data and is suitable for complex nonlinear systems.

Since it does not need a precise mathematical model, it can adjust the parameter values of PID in real time to make up for the shortcomings of the traditional PID algorithm. In upper limb rehabilitation training, the fuzzy PID controller can adaptively adjust the damping and stiffness coefficients using fuzzy reasoning according to the human-machine interaction force and the system error to change the training intensity and realize the on-demand auxiliary control of the rehabilitation robot. This adaptive adjustment capability enables the rehabilitation robot to provide personalized rehabilitation training according to the muscle strength differences and rehabilitation needs of different patients [4].

Zhengzhou University, Gao Jian et al. combined traditional control strategies with fuzzy logic to regulate the natural frequency ωn based on rehabilitation expertise and fuzzy control. When the patient deviates from the given path, the stiffness of the robot system increases; conversely, the stiffness of the robot system should decrease. This method can improve the safety of rehabilitation training and prevent patients from secondary injuries. Considering the force error of human-robot interaction, it is necessary to adjust the guide parameters in real-time according to different patients' disease levels through the two-parameter indexes of force error and change rate of force error in order to achieve the desired rehabilitation effect.

The team's fuzzy rule table is plotted against the fuzzy inference input/output relationship surface as follows (Table 1):

Table 1. Fuzzy rules

ef	ωn				
	ef=PB	ef=PB	ef=0	ef=NS	ef=NB
PB	ES	ES	ES	S	EB
PS	ES	ES	ES	M	B
PZ	ES	ES	ES	ES	M
NZ	S	ES	ES	ES	ES
NS	B	M	ES	M	B
NB	EB	S	ES	B	ES

*Ef is human-computer interaction (HCI) force errorēf is the rate of change of HCI force error; PB means positiveand and big; PS means positive and small, PZ means positive and zero; NZ means negative and zero; NS means nagtive and small, NB means nagtive and big; ES means extremly small, EB means extremly big; B means big, S means small, M means medium.

3.2. Neural network

Neural networks in upper limb rehabilitation training trajectory planning and control can achieve personalized rehabilitation program customization by learning the patient's movement data. It can identify and predict the patient's movement intention, so as to optimize the trajectory of the rehabilitation training and make it more in line with the patient's actual situation and rehabilitation needs. In addition, the neural network can improve the precision and efficiency of rehabilitation training through pattern recognition and deep learning techniques, helping patients recover upper limb function more effectively.

Haifang Mu's team introduced neural networks into the impedance control module, which ensures that the rehabilitation robot can flexibly adjust the stiffness and damping parameters according to the patient's rehabilitation progress by real-time adjusting the impedance parameters as well as the fuzzy controller's input variables $\Delta\theta$ and $\Delta\theta$ (Fig. 1) [3].

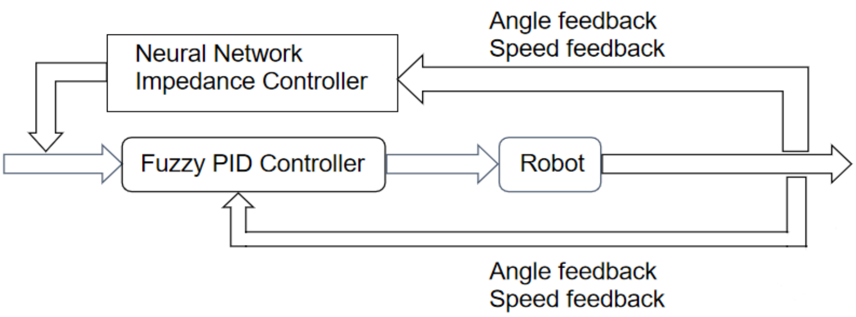

Figure 1. Fuzzy PID controller

At the later stage of remission and active training, Mu's team proposed a neural network-based impedance controller to adjust impedance parameters in real time to adapt to the progress of the rehabilitation of the affected limb.

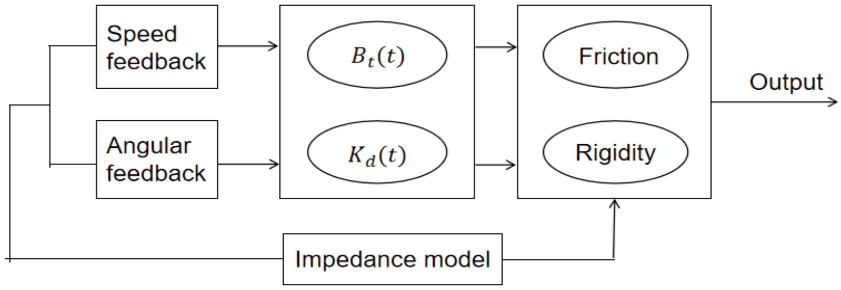

Figure 2. Neural Network Impedance

As shown in Fig. 2, the neural network impedance controller consists of a stiffness controller and a damping controller, where the input variables of the stiffness controller are the force deviation Δf and the angular deviation Δθ, and the output is the variable stiffness quantity Δad (t), and the input variables of the damping controller are the force deviation Δf and the velocity deviation Δθ', and the output is the variable resistance quantity Bd (t).

The FNN controller, or fuzzy neural network controller, is a control technique that combines fuzzy logic and neural networks. It utilizes the ability of fuzzy logic to deal with uncertainty and nonlinear problems, as well as the learning ability and adaptability of neural networks, in order to achieve efficient control of complex systems.

As shown in Fig. 3, the structure of the FNN impedance controller of Mu Haifang's team [5, 6].

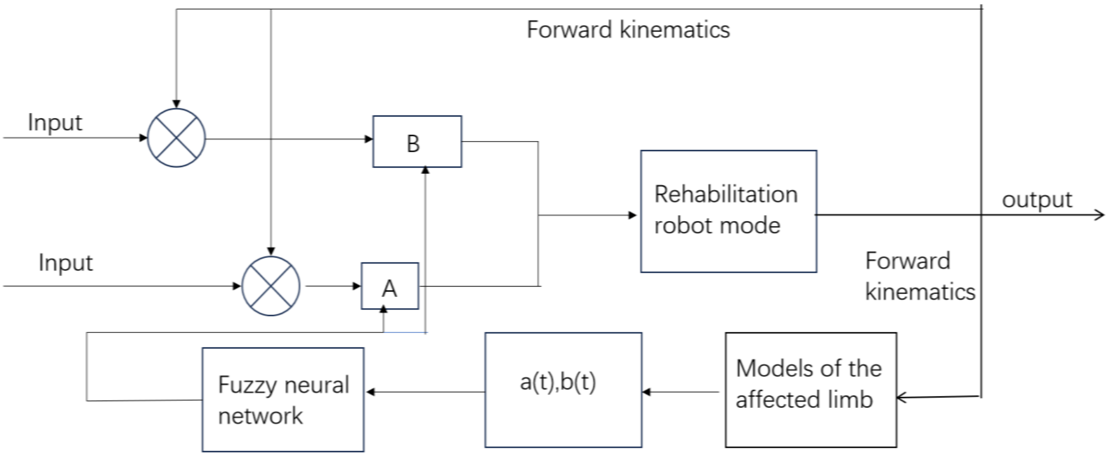

Figure 3. FNN Impedance Controller Structure

Yu Shiwei et al. designed an adaptive control method for upper limb exoskeleton rehabilitation robots based on the RBF neural network, which significantly improved the control accuracy and dynamic response of the system and successfully improved the original control basis (Fig. 4).

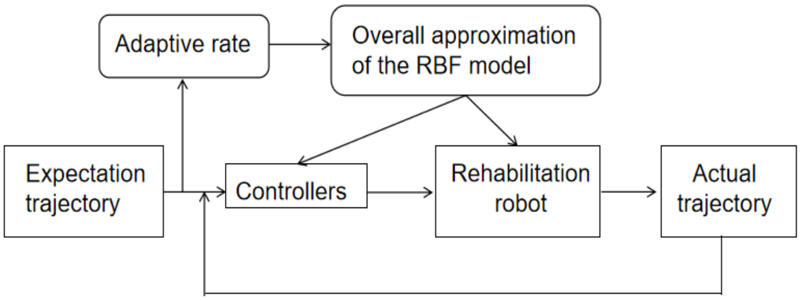

Figure 4. Block diagram of RBF control system

3.3. Human-computer interaction

The role of human-computer interaction in the upper limb rehabilitation training trajectory control is crucial. Through human-computer interaction, the rehabilitation robot can not only respond to the patient's movement intention in real-time and provide more efficient and personalized rehabilitation training programs, but also improve the patient's participation and enthusiasm, and enhance the patient's rehabilitation effect through interactive training. In addition, human-computer interaction can monitor and evaluate the patient's rehabilitation process, and adjust the difficulty and intensity of rehabilitation training according to the actual situation of the patient. In addition, the application of human-computer interaction technology, such as the control strategy based on surface EMG signals, also enables the robot to supervise and control the patient's limb movement in a more detailed way and improves the flexibility and sensitivity of rehabilitation training. Therefore, human-computer interaction plays the role of a bridge in upper limb rehabilitation training, connecting patients and rehabilitation equipment to achieve more efficient and personalized rehabilitation training [7-9].

Rongbin Tan and Shouyin Lu from Shandong University of Architecture proposed a human-computer interaction control method based on interaction force signals, focusing on the acquisition of the patient's movement intention through sensors to complete the active interaction of upper limb rehabilitation training [10]. The patient has a certain degree of mobility after entering the spasticity stage, in order to improve the patient's sense of participation in the training, the interaction force between man and machine is obtained by installing force sensors at the contact points of the human upper limb and several major joints, and the interaction force signals are transmitted to the sensors. When the interaction force signal collected by the sensor exceeds the set value, the current state of the robotic arm is obtained through the angular displacement, angular velocity and angular acceleration sensors, and the human's intention to adjust is classified and predicted to the next spatial working point, and the trajectory planning and control of the robotic arm to realize the adjustment and feedback through the current working point and the dynamic information to the prediction of the point information, and the process is shown in Fig. 5.

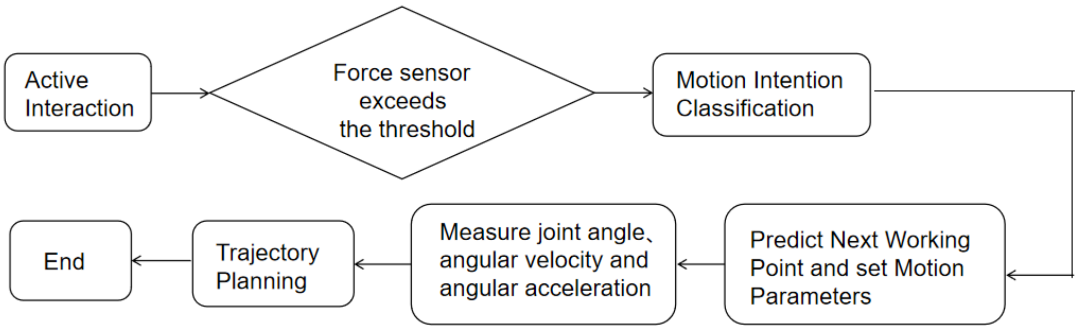

Figure 5. Active Interaction Flowchart

4. Result

Multimodal technology is a technology that utilizes and fuses data from multiple perceptual modalities for information processing and understanding. By fusing data from different modalities, the machine's ability to understand and process complex environments and information can be enhanced. Based on the analysis of this research, an upper limb rehabilitation training control method that integrates the use of multimodality, human-machine interaction and neural network is proposed. The sensors to sense the interaction force between the muscle and the machine, neuroelectric signals, and language and then use the fuzzy neural network controller to analyze and judge, to improve the robustness and stability.

Finally, the learning model is continuously reinforced by machine learning. Neural networks have strong nonlinear fitting capabilities and can handle complex pattern recognition and prediction tasks. The advantages of reinforcement learning lie in its ability to handle complex decision problems, adapt to dynamic and unknown environments, not rely on labeled data, and have strong adaptive and exploratory capabilities. Integrating and optimizing the two methods based on human-computer interaction can achieve more accurate and efficient completion of rehabilitation training trajectory motion control.

However, the core of multimodal technology lies in how to effectively integrate data from different modalities, overcome the differences and heterogeneity between modalities, and make full use of their respective advantages to achieve better performance and effects than a single modality. This is a difficult point in the process of practicing the method in concrete. At the same time, due to the lack of practice of the method, it thus has some limitations, such as lower sensor accuracy, insufficient real-time and the patient's feedback being complex and nonlinear. Therefore, there may be a problem that the methods cannot be reasonably integrated with the real implementation, and further experiments are still needed (Fig. 6).

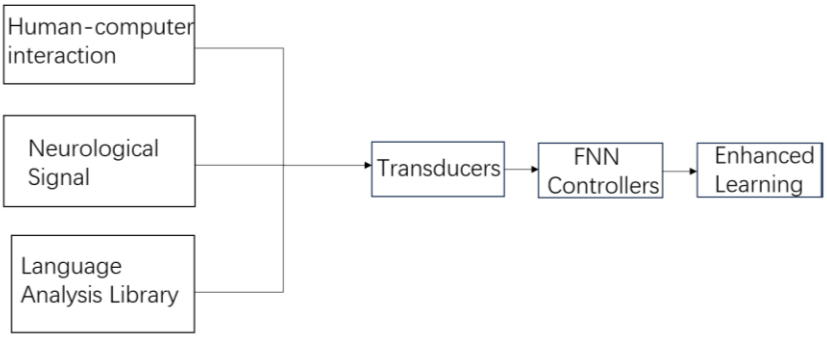

Figure 6. Optimization Flowchart

5. Conclusion

This paper summarizes several optimized control methods, including fuzzy PID, neural network technology, and human-machine interaction, by analyzing the PID control and impedance control of the upper limb rehabilitation training robot. These methods can adjust the control parameters in real time to adapt to the patient's rehabilitation progress and individual differences. In addition, this paper emphasizes the importance of multiple human-computer interaction methods and reinforcement learning in rehabilitation training and proposes the design of a rehabilitation training robot with multiple integrated optimization methods to improve patient participation and rehabilitation effects. Finally, we conclude that combining advanced control techniques with multiple optimization methods can significantly improve the performance of upper limb rehabilitation training robots to provide safer and more effective rehabilitation training for patients. Future research could further explore the integration and optimization of these technologies to achieve more personalized rehabilitation treatment plans.

References

[1] CHEN Guiliang, GUO Jian, LIU Gengqian. PID and control of knee joint dynamics analysis for lower limb rehabilitation robot. Journal of Hebei University of Technology, 2013, 42 (05): 71 - 76.

[2] YANG Dayong, TIAN Zhilin, RAO Xiaowei, et al. Adaptive force tracking upper limb active rehabilitation training robot control method based on impedance online identification [C]//Chinese Society of Automation. Proceedings of the 37th Annual Youth Conference of the Chinese Society of Automation (YAC2022). College of Advanced Manufacturing, Nanchang University; 2022: 8.

[3] H.F. Mu, K. Guo, B. Hu. Fuzzy PID and neural network impedance control of rehabilitation robot upper limb. Journal of Jining College, 2022, 43 (02): 89 - 92+97.

[4] Gao JJ, Liu LQ, Wang J, et al. Fuzzy control based variable conductance control for upper limb rehabilitation robot. Journal of Zhengzhou University (Engineering Edition), 2024, 45 (01): 12 - 20.

[5] H.F. Mu, K. Guo, B. Hu. Upper limb impedance control of rehabilitation robot based on genetic algorithm and fuzzy neural network. Journal of Langfang Normal College (Natural Science Edition), 2021, 21 (04): 56 - 59+64.

[6] YU Shiwei, LU Shouyin, LI Zhipeng, et al. Adaptive control method for upper limb exoskeleton rehabilitation robot based on RBF neural network. Computer Age, 2023, (10): 83 - 88.

[7] Wang YC. Structural design and supple control strategy of upper limb exoskeleton rehabilitation robot. Beijing University of Posts and Telecommunications, 2023.

[8] Zhang Shun, Shan Quan, Huang Jiancong, et al. Passive flexibility control of arm-wrist hybrid upper limb rehabilitation robot. Chinese Journal of Engineering Machinery, 2024, 22 (04): 468 - 473.

[9] Shanshan Hu. A three-degree-of-freedom upper limb rehabilitation training system based on adaptive on-demand assistance. Southeast University, 2022.DOI: 10.27014/d.cnki.gdnau.2022.002663.

[10] Rongbin Tan, Shouyin Lu, Weijie Xu, et al. Path planning of upper limb exoskeleton training and rehabilitation robot based on human-robot interaction. Manufacturing Automation, 2022, 44 (11): 58 - 63.