Research on Iterative Learning Neural Network Control for Manipulator

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Abstract: with the rapid development of science and technology, robot technology has also developed rapidly and is widely used in various industries, such as industry, aerospace, military, medical and other industries. The robotic arm is a mechanical device that simulates a human arm, and is the main execution mechanism of a robot. The manipulator system itself is a complex system with nonlinear, strong coupling and interference. Moreover, in practice, due to the very complicated working conditions, it is difficult to establish an accurate mathematical model of the robotic arm system, such as uncertain load, uncertain system parameters, or even no model at all. In addition, the transmission system from the output shaft of the motor to the execution axis of the robot arm inevitably produces flexibility, so the control of the robot arm considering the flexibility of the joint has also become a hot and difficult point of research. In addition, in order to save costs or reduce measurement errors, the robotic arm in industrial applications cannot measure some state variables. Designing an observer has also become an important part of the controller design. The research in this paper first considers a sliding mode adaptive controller based on a first-order filter observer under the conditions of uncertain system parameters and some state quantities that cannot be measured. Finally, based on the completely model-free situation in the actual process, an adaptive observer of bp neural network is designed, and based on the universal approximation principle of nonlinear terms of the neural network, the inversion control method is adopted the tracking of the movement track of the robot arm is realized.

1. Introduction

Iterative learning control is a control technique used to improve the transient response and tracking characteristics of a process, machine, device or system with repetitive motion characteristics. Its basic idea is to correct the unsatisfactory control signal by the deviation between the actual output and the expected output of the system, and generate a new control signal to improve the tracking performance of the system. The ILC provides a very good object for objects with strong nonlinearity, strong coupling, difficult modeling, and high-precision trajectory control requirements, especially objects with repetitive motion characteristics (such as industrial robots, CNC machine tools, chemical processes, etc.) Control Method. The current research focus of iterative learning control is mostly focused on the study of iterative learning rate. Once the actual system faces a new environment and control task, the system must relearn, that is, the existing iterative learning control method for a specific trajectory tracking problem It has a good control effect. The learning result is the control input u (t) under memory. Once the output trajectory is expected to change, it must be re-learned. Therefore, it belongs to “remembering” learning. That is, the learning control process depends on some information that seems to be known but actually unknown ud (t), and how to make full use of all the information of the control system's previous control experience, and the use of this information and the convergence of the learning control process Relationships are the key to research. The current practice of selecting the initial control amount: part of the application is to select a constant value as the initial control amount; another part of the application is to select the control amount at the end of the previous iterative learning as the initial control amount of the task, and then rely entirely on the learning rate algorithm Amended. The consequence of this is that in the first cycle of a new running task, the control amount has absolutely no effect on the output of the system, and even has a negative effect, greatly increasing the learning time and the number of cycles.

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2. Motion Control of Rigid Joint Manipulator

The multi-link rigid manipulator system is a complex multi-input multi-output nonlinear system with time-varying, strong coupling and highly nonlinear dynamic characteristics. It has a wide range of work, complex changes in working conditions, and unavoidable uncertainties such as interference and unmodeling in actual engineering applications. At the same time, due to factors such as cost and hardware installation, it is difficult to measure the global state vector. For example, in order to reduce the cost of actual commercialized industrial robots, only position sensors are used. In this way, high-speed noise is easily introduced by using speed signals obtained by position differentiation. Therefore, highly robust controllers have always been the focus of research in the field of robot control. Reference used a non-linear disturbance observer to observe the uncertainty and disturbance of the system, and designed an adaptive inversion sliding mode control strategy, which is measurable in the global state vector, and the disturbance is a slow variable, that is, the interference term pair Under the condition that the time derivative is 0, the robot arm position tracking control is realized. Literature proposed an adaptive output feedback control method based on neural network. The controller consists of three control items based on dynamic compensator output feedback, neural network adaptation and robustness. Based on the nominal model of the system, Complete the tracking and control of the end position and speed of the robot arm. References proposed the model-free manipulator trajectory tracking control strategy by taking advantage of the positive definite boundedness of the inertial matrix in the manipulator dynamics system. neural networks were used as controllers, and the ability of non-linear mapping was used to approximate various unknown non-linear terms. At the same time, robust errors were added to the control law to eliminate approximation errors. Reference designed a new adaptive neural controller using deterministic learning theory, which not only achieves the final consistent and boundedness of all signals of the closed-loop system, but also guarantees the convergence of some neural network weights and unknowns during stable control. Dynamic local approximation of closed-loop systems. The above research is also based on the condition that the global state of the system is measurable. The introduction of the correction term in the weight adaptive law improves the approximation accuracy and robustness of the neural network; the approximation model is then directly applied to the inversion control design process, in order to avoid the calculation of the intermediate virtual control signal in the inversion method The expansion of the differential term of the system equations caused dynamic surface control technology.

3. State Observation and Inversion Tracking Control of Neural Network

The controller used in the above is only suitable for situations where the parameters are unknown and some state quantities are unknown, but cannot be used for more complicated situations, such as the dynamic model of the system is difficult to establish in conventional modeling or more external environmental impact factor. So in this case, it is quite necessary to design a more effective and reliable controller design. In this section, the inversion control design method is used to fully consider the actual situation of system uncertainty and disturbance, and a model-free robotic arm output feedback control design strategy is proposed. Applying the design method of nonlinear system observer, the output feedback speed state observer based on neural network is first designed. Aiming at the friction damping and uncertain model parameters, a model-free output feedback controller based on neural network observer is proposed for multi-link manipulators by using inverse control design strategy. A state observer is designed using BP neural network to approximate the system model online. The weight of the neural network is adjusted online by the back-propagation algorithm. The introduction of correction terms enhances the robustness of the observer. Based on this, an inversion tracking controller based on the observation state and model is designed. The Lyapunov stability theory proves that the controller can guarantee the boundedness of the tracking error and the boundedness of all signals in the closed-loop system.

The inversion control (also known as backstepping control) design method introduces virtual control to decompose a complex nonlinear system into multiple simpler and lower-order systems, and then selects the appropriate Lyapunov function to ensure the stability of the system. And gradually derive the final control rate and parameter adaptive law to achieve effective control and global adjustment of the system. Therefore, the inversion design method has attracted great attention from scholars in recent years.

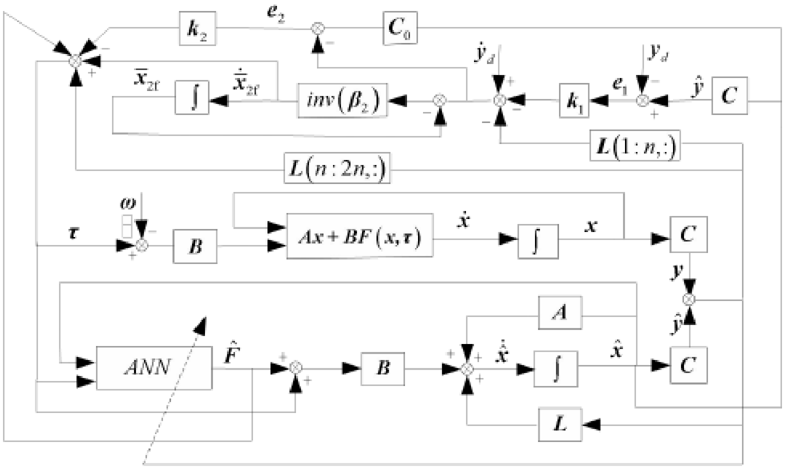

Fig.1 Overall Control Structure

4. Fuzzy Neural Network Observer and Its Inversion Control

The RBF neural network can realize the estimation of the speed state of the manipulator without the speed measurement and the model. However, it uses an observer designed under the assumption of strict positive reality, so there is a certain rigorous theoretical derivation process in the process of designing the controller. Because the neural network has strong self-learning and association capabilities, it cannot process and describe fuzzy information, and requires a high sample size. The fuzzy system has a reasoning process that is easy to understand, but it requires a lower sample size, slower inference speed, lower accuracy, and adaptive learning is difficult to achieve. Therefore, for situations such as this, a fuzzy neural network control strategy is proposed by combining the advantages of both in this section. Among the multi-degree-of-freedom robot arms, the motor and the driven robot arm are connected for transmission through a reducer. Harmonic speed reducers are more commonly used in robots, and this type of reducer has some flexibility. In addition, harmonic reducers are difficult to express with mathematical models. When position and speed sensors are not installed at the end of the connecting rod, a state observer needs to be designed to estimate signals that cannot be directly measured. In the previous section, for the flexible manipulator, it was mentioned that the tracking control was implemented by means of singular perturbation. Another method is used in this section, which is inversion control. The fuzzy neural network is used to approximate the unknown nonlinear term F (x). The basic structure of a fuzzy system consists of IF-THEN rules and fuzzy inference mechanisms. Using the advantages of fuzzy systems and neural networks, a four-layer fuzzy neural network is used to approximate unknown nonlinear terms.

A flexible coupling is added to the rigid robotic arm to make the system more complicated. In the beginning of this chapter, the general control method is adopted in the case of large flexibility. It is difficult to control the flexible mechanical arm and it is prone to jitter. In order to solve this problem, a flexible compensation or filtering method is used to achieve Precise trajectory tracking control for flexible robotic arms. Afterwards, an RBF neural network control method was adopted for the model-less and speed-sensor-free flexible robotic arm to achieve accurate estimation of the state quantity of the observer. Finally, the problem of sensorless at the connecting rod end of the modelless flexible robotic arm is proposed. A fuzzy neural network observer is designed to estimate the state quantity, and the inverse control method is used to realize the sensorless connection at the connecting rod end. Case tracking. In addition, computer simulations performed by Simulink verified the control strategy under corresponding conditions, and the experimental results and analysis showed that the accuracy and effectiveness of the control algorithm studied.

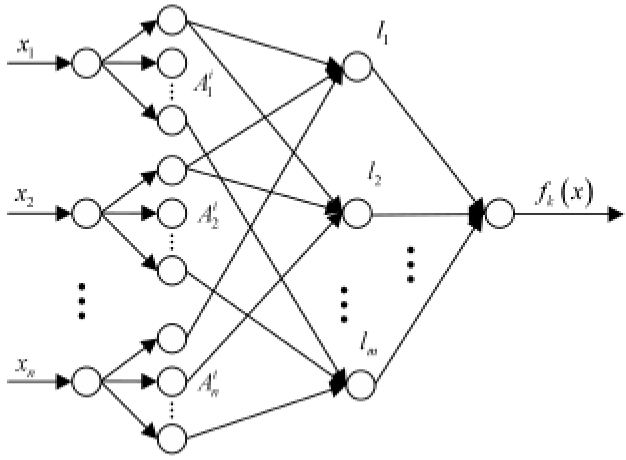

Fig.2 Structure of Fuzzy Neural Network

5. Conclusion

This paper uses a combination of theory and experiment to propose a variety of control strategies for complex manipulators in practical engineering applications. Through more intelligent control methods, some previous control accuracy and motion processes caused by models and environmental problems are insufficient. Frequent debugging issues. However, the selection of some parameters in the intelligent control process comes from the relevant literature and program debugging process, which is not optimal. Therefore, in combination with the control optimization method, the control parameters are optimized to achieve more accurate control accuracy and faster control speed. In addition, signal processing methods, such as good time-frequency resolution performance of wavelet analysis, can also be combined to improve the approximation accuracy of the neural network.

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References

[1] Wang Wenzheng, Wang Xiaolan. Research on Robot Arm Motion Control Based on Genetic Dual Mapping Neural Network [J]. Journal of Gansu Sciences, 2006 (02): 81-84.

[2] Liu Yibiao, Chen Jun. Research on trajectory error of manipulator based on radial basis function neural network control [J]. Machine Tool & Hydraulics, 2018, v.46; No.465 (15): 112-115.

[3] Zhou Fang, Zhu Qidan, Cai Chengtao, et al. Neural Network Control of Manipulator Position / Force Based on Observer [J]. Journal of Huazhong University of Science and Technology (Natural Science Edition), 2009 (07): 84-87.

[4] Wang Wenji. Research on Intelligent Control Strategy of a Neural Network Composite Robotic Arm [J]. Gansu Science and Technology, 2006, 22 (9): 108-109.

[5] He Guangping, Lu Zhen, Wang Fengxiang. Neural Network Optimal Control of Manipulators on Redundant Satellites [J]. Control Theory & Applications, 2001, 18 (5): 759-764.