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Innovative Application of Deep Learning Driven Active Disturbance Rejection Control Technology in Motor Speed Regulation

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Abstract

With the increasing complexity of motor speed control system, the traditional active disturbance rejection control method has performance limitations when dealing with nonlinear, time-varying and strong coupling systems. This paper studies the combination of deep learning and active disturbance rejection control technology, and proposes an active disturbance rejection control algorithm based on deep learning, which can adaptively optimize system parameters and improve the suppression ability of complex disturbances. The design and implementation of the algorithm in motor speed regulation combines the nonlinear feature extraction ability of deep learning and the fast response characteristics of active disturbance rejection control. The experimental results show that the active disturbance rejection control system based on deep learning has improved the motor speed regulation accuracy, dynamic response speed and anti-interference ability, and shows better robustness and stability especially in complex working conditions.

Keywords

Active Disturbance Rejection Control; Deep Learning; Motor Speed Regulation; Nonlinear System.

1. Introduction

Traditional motor speed control methods, such as PID control and fuzzy control, show good results in simple systems, but it is difficult to ensure ideal control results in the face of nonlinear, time-varying and complex working conditions in actual systems. As an advanced control method of active compensation disturbance, active disturbance rejection control technology has strong anti-interference ability and robustness, and has gradually become an important means in the field of motor speed control. As a data-driven intelligent technology, deep learning has shown excellent capabilities in pattern recognition, complex function approximation and adaptive optimization, which provides a new solution for improving the performance of control systems. The combination of deep learning and active disturbance rejection control can effectively improve the adaptability of the system to uncertainties and disturbances, so as to achieve higher control accuracy and better dynamic response in complex application scenarios such as motor speed regulation.

2. Principle and Development of ADRC Technology

2.1 Basic Principle of Active Disturbance Rejection Control

Since its introduction, Active Disturbance Rejection Control (ADRC) has become the core technology in many control systems because of its excellent anti-interference ability and robustness.

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Early studies focused on the formulation of the theory of ADRC and its application to simple linear systems. However, with the expansion of application fields, especially in the fields of motor speed regulation, robot control and unmanned driving, ADRC has gradually exposed its limitations in dealing with high nonlinearity, time-varying characteristics and complex disturbances. Therefore, researchers have proposed a variety of improvement schemes, including adaptive control, the combination of fuzzy control and neural network control.

With the help of big data training, deep learning can learn the dynamic characteristics of the system without accurate system models, which is especially suitable for dealing with complex nonlinear and high-dimensional systems. Many research works have begun to explore the combination of deep neural networks (DNN) and deep reinforcement learning (DRL) with active disturbance rejection control techniques to improve the adaptability and control accuracy of the system to complex disturbances.

The basic principle of ADRC is to introduce an extended state observer to estimate the disturbance of the system in real time and use this information to compensate, so as to achieve accurate control of the system. The core idea of ADRC is to treat the system disturbances and uncertainties as extended states, and estimate these states and feed back to the controller for compensation, so as to effectively improve the system performance. The basic structure of ADRC consists of an extended state observer, a nonlinear dynamic compensator and a linear feedback controller. The role of the extended state observer is to estimate the system state and disturbance online. Suppose the dynamic equation of the system is as follows:

$$\dot{x}(t) = Ax(t) + Bu(t) + d(t) \tag{1}$$

Where, $\dot{x}(t)$ is the system state vector, $u(t)$ is the control input, and d(t) represents the disturbance or external disturbance of the system. The key of ADRC is how to estimate the disturbance d(t) and compensate it. The extended state observer works by introducing an extended state variable, defined as:

$$\widetilde{d}(t) = \dot{x}(t) - Ax(t) - Bu(t) \tag{2}$$

Observer to estimate $\widetilde{d}(t)$, can compensate the impact of the disturbance on the system in real time without completely relying on the system model. The output of the extended state observer will be passed to the nonlinear compensator, which adjusts the control system according to the observed disturbance, so as to realize the tracking of the system state and the realization of the control target[1].

2.2 The Core Structure and Implementation Mechanism of ADRC Algorithm

The core structure of ADRC algorithm is mainly composed of extended state observer (ESO), nonlinear disturbance compensator, controller and their mutual cooperation mechanism. The extended state observer is used to estimate the system state and external disturbance online. The basic structure of the extended state observer is to combine the dynamic model of the system with the disturbance term, compensate through the feedback loop, and finally optimize the system performance. The mathematical model of ESO is expressed as follows:

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - C\hat{x}) \tag{3}$$

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Where, $\hat{x}$ denotes the estimated system state,L is the observed gain, y is the system output, and C is the output matrix. The core idea of the nonlinear disturbance compensator is to use the disturbance estimated in real time to compensate the output of the controller. The controller adjusts the control signal through the feedback mechanism to suppress the influence of the disturbance on the system. The specific control input is expressed as follows:

$$u = - Kx - \widehat{d} \tag{4}$$

Where, K is the control gain matrix and $\widehat{d}$ is the disturbance estimated by the extended state observer. The control input not only depends on the system state, but also considers the compensation of the disturbance, so as to realize the active suppression of the disturbance[2].

2.3 Application Exploration of Deep Learning in Active Disturbance Rejection Control

The application exploration of deep learning in active disturbance rejection control mainly focuses on nonlinear modeling of optimization system, disturbance estimation and adaptive adjustment of control parameters. Traditional ADRC algorithms rely on accurate system models and real-time estimation of disturbances, but in practical engineering applications, due to the high nonlinearity and complexity of the system, the traditional methods are often difficult to meet the requirements. Trained on a large amount of data, deep learning can automatically capture complex nonlinear relationships in the system, thus playing an important role in controller design and disturbance compensation. For example, in the motor speed control system, deep neural networks are used to learn the dynamic characteristics of the motor and help optimize the parameters of the extended state observer, so that the controller can maintain good performance under various dynamic conditions.

In some applications, the conventional ESO may suffer from estimation bias when dealing with a wide range of disturbances or abrupt disturbances, which affects the control accuracy. Using the neural network model of deep learning, the accuracy of disturbance estimation can be enhanced, especially in the case of large changes in disturbance amplitude, and the deep learning model is able to capture the disturbance pattern by learning historical data to improve the performance of ADRC.

3. Application Innovation of ADRC Technology in Motor Speed Regulation

3.1 Optimization of Active Disturbance Rejection Control Performance by Deep Learning Model

Deep learning has been used in many control systems, especially in the modeling and optimization of complex systems. Deep neural networks (DNN) and convolutional neural networks (CNN) have become common tools in many intelligent control systems due to their powerful feature extraction and nonlinear modeling capabilities. Compared with traditional control methods, deep learning algorithms show significant advantages in dealing with high-dimensional, time-varying and uncertain systems.

In the application of ADRC, deep learning is mainly applied to the optimization of nonlinear modeling and disturbance estimation. Many researchers use deep neural networks to replace the traditional extended state observer to improve the system's ability to identify nonlinear disturbances. Deep Reinforcement learning (DRL) is widely used to automatically adjust the control strategy and optimize the control parameters to further improve the dynamic response ability of the system. Although deep learning has shown promising potential in control systems, it still faces some challenges in practical applications. For example, the training of deep learning models requires a large amount of data and computing resources, and may encounter problems such as overfitting during the training process.

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Active Disturbance Rejection control (ADRC) relies on mathematical model and model error estimation. When dealing with strongly nonlinear and high-dimensional complex systems, ADRC often faces problems such as insufficient accuracy of disturbance estimation and difficulty in adjusting system parameters. Deep learning technology has powerful data-driven characteristics, which can automatically learn the dynamic characteristics of the system, accurately identify complex disturbances, and adaptively adjust. The neural network in the optimization method based on deep learning is used to model the nonlinear behavior of the motor system, and the back propagation algorithm is used to adjust the weight of the network to improve the recognition ability of the model for disturbances under different working conditions. In practical applications, deep learning can sense and predict factors such as nonlinear load changes, external disturbances and system parameter uncertainties in the process of motor speed regulation in real time.

3.2 Design and Implementation of Active Disturbance Rejection Control Algorithm for Deep Learning

In the motor speed regulation system, the design idea of the active disturbance rejection control algorithm based on deep learning is mainly divided into two parts. First, the deep learning model is used for disturbance estimation and prediction. The other is to combine the deep learning results with the disturbance compensation mechanism of ADRC to adjust the real-time control strategy. In the system design, it is necessary to establish the mathematical model of motor speed regulation, including the motor dynamic equation, load model and the expression of external disturbance. The neural network model based on deep learning is trained using the real-time data of the system to obtain the nonlinear characteristics and disturbance information of the motor under different working conditions. In terms of network structure, multi-layer Perceptron (MLP) or Long Short-Term Memory (LSTM) networks are used, which can process time series data and model complex nonlinear relationships[3].

After the design is completed, the deep learning model is embedded into the ADRC framework for real-time monitoring, analysis and optimization of the input and output signals of the motor system. In the specific implementation, the training process based on gradient descent method is used to optimize the loss function of the network and improve the perception and control ability of the disturbance. In the design of the controller, the output result of the deep learning model is used as the disturbance estimation value in the active disturbance rejection controller, and then the control quantity is calculated to compensate the external disturbance and model error in real time, so as to ensure the stability and efficiency of the motor system under various working conditions. The implementation of the algorithm requires not only an efficient neural network model, but also optimization on the hardware platform to ensure the real-time performance and computational efficiency of the algorithm.

3.3 Experiment and Result Analysis

A high-precision DC motor system is used in the experimental environment, which is equipped with load simulation device and high-speed data acquisition equipment. System parameters such as motor speed, current and load torque are collected and input to the control system in real time. The experimental results show that the ADRC driven by deep learning shows significant advantages in motor speed regulation accuracy, dynamic response speed and anti-interference ability.

In the experiment of anti-interference ability, external disturbances with different amplitudes (such as load mutation, power supply fluctuation, etc.) were applied, and the results show that the ADRC driven by deep learning maintains good system performance under all kinds of disturbances. The experimental data show that, compared with the traditional PID and ADRC control, the motor speed fluctuation amplitude is reduced by about 18% and 12% when the disturbance amplitude is 20% and 50% of the load change. In addition, in terms of the dynamic response speed, the recovery time of the deep learning-driven controller is about 1.2 seconds when it is subject to a burst disturbance, which is significantly better than the 2.5 seconds of PID control and the 1.8 seconds of traditional ADRC control.

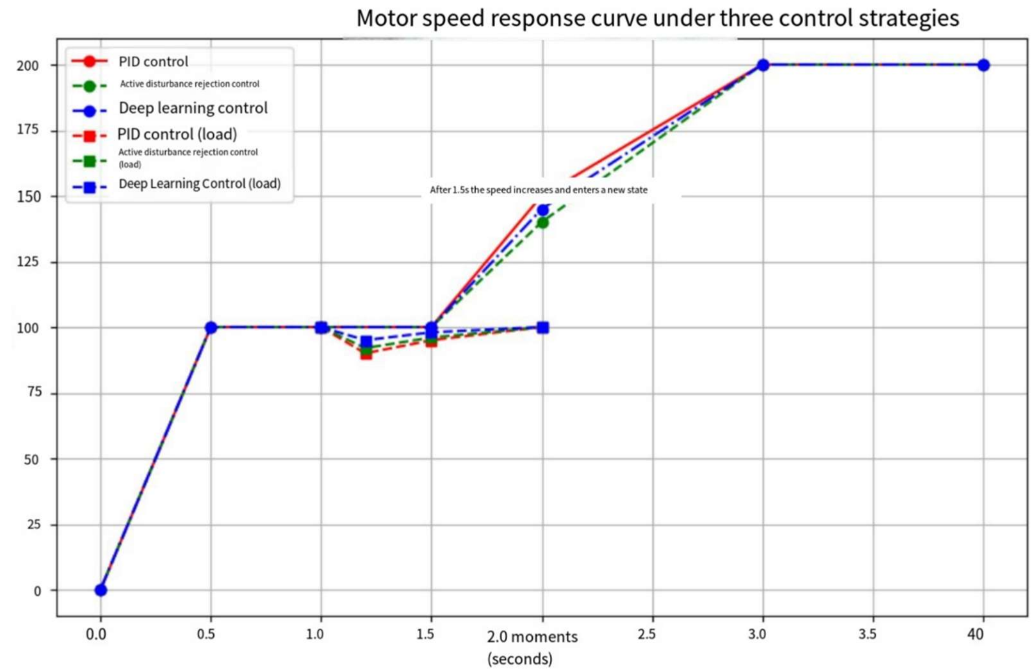

Figure 1. Comparison of motor speed response curves under three control strategies

At 0.5s, the PID control motor speed has reached 100RPM, and at about 1s, the speed rises to 106RPM. The ADRC control system has a rotational speed of 101RPM at 1 second, which is closer to the set point than the PID control of 106RPM. The deep learning driven ADRC reaches 100RPM at 0.5 seconds. The speed increase after 1.5 seconds signals that the controller has entered a new state to cope with possible external disturbances or load changes. The response waveform after the load is applied at 100 RPM can be seen that the PID control quickly reaches 100 RPM at 0.5 seconds, but rises to 106 RPM after the load is applied (about 1 second), with a certain overshoot. The ADRC reaches 101 RPM at 1 second, which is less affected by the load change and maintains a small deviation, indicating a stronger disturbance rejection capability. The deep learning control already reaches 100 RPM at 0.5 seconds, which is the fastest response while having the smallest fluctuation and optimal adaptability to the load.

4. Conclusion

The research in this paper successfully combines deep learning technology with Active Disturbance Rejection Control (ADRC) to improve the performance of motor speed control system. With the introduction of deep learning models, ADRC is able to deal with nonlinearity and uncertainty more effectively, resulting in significant improvements in dynamic response and disturbance immunity. Experimental results show that the ADRC driven by deep learning is superior to the traditional control method in response speed and accuracy. In addition, the technology shows good adaptability and robustness in practical applications, which brings a new solution to the field of motor speed regulation. In general, the ADRC technology driven by deep learning provides new ideas and methods for the development of motor speed control systems.

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