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Research on Intelligent Control of Flexible Joint Manipulator under Dynamic Pattern Recognition

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ABSTRACT. *Pattern recognition combined with control theory is the key direction that has attracted the attention of many scholars in academic circles in recent years. Based on the learning theory, this paper will develop the research on intelligent control of flexible joint manipulator based on dynamic pattern, and take the flexible joint manipulator dynamics model as the main object of research control is studied. The dynamic analysis of the closed-loop system dynamics and the reference trajectory of the control system is studied, and the flexible joint manipulator control system is realized by the complex tracking person.*

KEYWORDS: *Dynamic mode; Flexible joint manipulator; Intelligent control*

1. Introduction

Research on control systems based on pattern recognition theory has been the focus of research in recent years. With the continuous improvement of the theory system of pattern recognition, the application of pattern recognition theory represented by neural network in real life is more and more common[1], and it also gives birth to the concept and practice of combining the knowledge of other disciplines with pattern recognition theory. Research on intelligent control based on dynamic pattern recognition has emerged. Therefore, this paper develops an intelligent control study of flexible joint manipulators under dynamic pattern recognition.

2. Mathematical Model of Flexible Joint Manipulator

The mathematical model of the flexible joint manipulator is established to facilitate the study of the positional relationship and the mechanical relationship between the various components in the manipulator in the control process. It is also called the dynamic study of the flexible joint manipulator. At present, the dynamic analysis methods commonly used in flexible joint manipulators include the

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Lagrangian equation and the Newton-Eulerian equation.

To facilitate the mathematical model derivation of the flexible joint manipulator[2], it is first assumed that the flexible unit of the joint is approximated as a linear spring. Let the rotation angle of the link at a joint be q1, and the rotation angle of the motor be q2, then the torque generated by the joint is K(q1-q2), and K represents the stiffness of the flexible joint. At this time, the elastic potential energy is V (q^1-q^2)=K(q^1-q^2)2/2.

Then, assume that the kinetic energy of the motor's rotation is only affected by the speed of the front link, independent of other factors. Since the moment of inertia of the connecting rod of the flexible joint arm is much larger than the moment of inertia of the motor, the influence of the link motion on the kinetic energy of the motor can be ignored. According to the above assumptions, it can be known that the motor has no influence on the rotational speed of the connecting rod. For a flexible joint robot arm with n degrees of freedom, the kinetic energy of the connecting rod is:

$$\text{T1(q1,q2)=}\ \frac{1}{2} q^{T}{}_{1} M_{1}(q_{1}) q_{1} \tag{1}$$

The total potential energy equation is:

$$V(q_1, q_2)\ \ \text{A=}\ \frac{1}{2}(q_2 - q_1)^T K(q_2 - q_1) + V_n(q_1) \tag{2}$$

3. Determine Learning Theory

3.1 Local Approximation Characteristics of Rbf Neural Networks

RBF neural network is one of the tools commonly used in the field of adaptive control in recent years for system unknown dynamic approximation[3]. RBF neural Ω_z network can approximate any continuous function f(z) with arbitrary precision in tight set. The expression formula is as follows:

$$f(Z) = W^T S(Z) + \varepsilon(Z), \text{A}Z \in \Omega_Z \in R^M \tag{3}$$

In the past literature, continuous excitation conditions have been difficult to pre-verify in the identification and control of nonlinear systems. According to the above lemma, RBF neural networks can achieve local accurate approximation of nonlinear systems under partial continuous excitation conditions. It is applied to the identification and adaptive control of nonlinear systems.

3.2 Dynamic Pattern Recognition

Dynamic pattern recognition is a method to realize the effective expression,

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similarity characterization and rapid identification of dynamic modes based on the approximation characteristics of RBF neural networks to the dynamics of nonlinear systems. Before the realization of the identification and recognition of dynamic modes, the definition of the concept of dynamic mode needs to be given. The identification process of the dynamic mode consists of an identification phase and an identification phase, wherein the identification refers to how to acquire an unknown feature in the dynamic mode, and the identification refers to how to determine the similarity between the measured mode and the recognized mode. According to the definition of learning theory, in order to realize the identification of the dynamic mode of the system (2-10), it is necessary to construct the following dynamic RBF neural network equation[4]:

$$\hat{x} = -A(\hat{x} - x) + \hat{W}^T S_A(x) \tag{4}$$

The dynamic system's system state changes with time, and when the initial conditions or system parameters change, the nonlinear system will produce different dynamic modes. Therefore, it is not feasible to judge the similarity between dynamic modes by using only the finite features such as the system state. . The research results in the nonlinear field indicate that the similarity between dynamic modes can be measured according to the similarity of its system dynamics. Therefore, according to the similarity definition of dynamic patterns, the establishment of dynamic pattern recognition mechanism and the study of pattern recognition strategies are carried out.

4. Adaptive Neural Network Learning Control

4.1 Based on Stable Adaptive Neural Network Control Acquisition and Storage of Empirical Knowledge

According to the structure of the stable adaptive neural network control system designed in the previous section, it is decomposed into two LTV perturbation subsystems, and then the regression characteristics of the system variables and the local neural network rights are proved by analyzing the stability of the subsystem. The convergence of values. Then the RBF neural network is used to obtain the empirical knowledge of the unknown dynamics along the periodic trajectory in the control system, and it is stored in the form of constant values for the reuse of the empirical knowledge in the subsequent neural network control design.

4.2 Neural Network Learning Control Based on Empirical Knowledge

According to the local accurate approximation characteristics of RBF neural network and the construction method of RBF neural network, the following constant value neural network controller is designed by taking the reference trajectory as an example for the same or similar control tasks:

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$$u = -z_3 - C_4 z_4 - \bar{W}_4^T S_4(\psi_4) \tag{10}$$

The weight matrix of the virtual control, because the neural network corresponds to the unknown dynamics of the system, similar to the proof of Theorem 3-1, another Lyapunov function is given here:

$$V' = \frac{1}{2}\sum_{i=1}^{4} z_i^T K_i z_i + \frac{1}{2}\sum_{i=1}^{3} y_i^T y_i \tag{11}$$

Theorem: Consider the closed-loop system consisting of the constant-mechanical arm model reference signal yd, the constructed constant-value neural network controller, and the Lyapunov function. For being able to generate periodic trajectories with Theorem 2 $\Psi_d(x_d(0))$ The same or similar reference trajectory whose initial state is $x_d(0)$,Given arbitrary constant $\mu > 0$,Bounded initial condition x(0) for any satisfaction $V'(0) \le \mu$,There are design parameters that keep all signals in the closed-loop system consistently bounded and guaranteed x(0) at $\Psi_d(x_d(0))$ tracking error in a small neighborhood can converge to a small neighborhood of zero.

5. Problem Description

5.1 Description of Neural Network Control Problem of Flexible Joint Manipulator Based on Determined Learning

Determining learning theory provides an effective way to solve the learning problems of control systems in dynamic environments. According to the learning theory, the local RBF neural network satisfying the local continuous excitation condition can realize the accurate approximation of the unknown dynamics of the nonlinear system with periodic or regression characteristics, thus realizing the dynamic learning of the closed-loop control system, and the knowledge gained from the experience. Used for the same or similar control tasks for better control. Based on the dynamic model of the flexible joint manipulator obtained in the previous section and the given reference trajectory mathematical model, a flexible joint manipulator neural network learning control system with parameter uncertainty is designed. In order to solve the problem of the increase of the input dimension in the neural network, the design of the constant value neural network controller based on the learning is not only to realize the progressive tracking of the reference signal by the angle vector of the mechanical arm link, but also to ensure that the tracking error is enough for a limited time. Convergence to a small neighborhood of zero. Before implementing the neural network control based on deterministic learning, this section first designs the adaptive neural network controller using the dynamic surface control design method, and then according to the deterministic learning theory, the local RBF neural network is under the condition that the neural network input is a periodic trajectory. With the characteristics of the system's unknown

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dynamic accuracy approximation ability, the empirical knowledge learned by the neural network in the controller for the unknown dynamic approximation of the system is saved in the form of constant value, and finally the obtained neural network weights are used to construct the constant value neural network. Controller.

5.2 Description of Research on Flexible Joint Manipulator Control Based on Dynamic Pattern Recognition

Dynamic pattern recognition is a method to realize the effective expression, similarity characterization and rapid identification of dynamic modes based on the approximation characteristics of RBF neural networks to the dynamics of nonlinear systems. This section will introduce how to construct a dynamic pattern recognition mechanism for the problem that the measured reference trajectory dynamic mode is unknown. It will involve the dynamic pattern recognition method mentioned in the second section, and design the appropriate recognition strategy according to the principle of the dynamic pattern recognition method. This strategy can not only realize the rapid recognition of the reference trajectory dynamic mode, but also solve the problem of how the system responds quickly when the reference trajectory occurs at a certain time point; then according to the design of the constant value neural network controller in the third section Method, construct a set of candidate constant value controller groups corresponding to different dynamic modes, and introduce the method of calling the controller after the system recognizes the reference trajectory mode, especially in the case of switching the reference trajectory mode, designing reasonable control The switching strategy is to ensure the good tracking performance and stability of the control system. Finally, the control simulation results of the two-link flexible joint manipulator are given to verify the effectiveness of the control scheme based on dynamic pattern recognition.

6. Dynamic Pattern Recognition Intelligent Control Achieves Results

6.1 adaptive Neural Network Dynamic Surface Control Design

(1) First set the tracking error:

$$z_1 = q_1 - y_d \tag{5}$$

According to this, you can ask for guidance $\dot{Z}_1 = \dot{q}_1 - \dot{y}_d$ Introducing new filter virtualization control variables $\alpha_{1f} \in R^n$ .And set the variable error $Z_2 = \dot{q}_1 - \alpha_{1f}$,Construct the virtual control formula as follows:

$$\alpha_1 = -C_1 z_1 + \dot{y}_d \tag{6}$$

(2)A known $\dot{Z}_1 = \dot{q}_1 - \dot{y}_d$,The formula for the differential equation is as follows:

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$$\begin{aligned}\dot{z}_2 &= M^{-1}(q_1)K(q_2 - q_1 - K^{-1}C(q_1, \dot{q}_1))\alpha_{1f} \\ &-K^{-1}g(q_1) - K^{-1}M(q_1)\dot{\alpha}_{1f} - K^{-1}C(q_1, \dot{q}_1)z_2)\end{aligned} \tag{7}$$

(3)A known $z_3 = q_2 - \alpha_{2f}$, the formula for the differential equation is as follows:

$$\dot{z}_3 = \dot{q}_2 - \dot{\alpha}_{2f} \tag{8}$$

The above steps are the same as the error variables obtained from the above design, and the following Lyapunov function is constructed:

$$V = \tfrac{1}{2}\sum_{i=1}^{4} z_i^T K_i z_i + \tfrac{1}{2}\sum_{i=1}^{2} tr[\tilde{w}_{2i}^T \Gamma_{2i}^{-1} \tilde{w}_{2i}] + \tfrac{1}{2}3\sum_{i=1}^{4} y_i^T y_i \tag{9}$$

According to the above analysis, the reason for the increase of the dimension of the neural network in the traditional design is mainly because there is a derivative term of the virtual control in the input, and the item is often related to the unknown parameter in the previous step. In this case, it is generally required. Instead of using the known set of state variables in the virtual control derivative term as the neural network input, the input dimension of the neural network also increases with the number of known state variables in the derivative term. The more serious situation is that the parameter unknowns that are approximated by constructing the RBF neural network in the previous step will appear again in the current step, so the RBF neural network needs to be constructed again in the current step to approximate the unknown. The increase of the system order is constantly appearing, and the redundancy of computation and the waste of computing resources are greatly increased, which greatly increases the computational burden of the neural network. The significance of the dynamic surface control design method is to avoid repeated modeling of the same unknown. By introducing the designed filter dummy variables, the parameter unknowns in each step will not appear in other steps, thus avoiding multiple steps to the same The occurrence of neural network approximation occurs when the parameter is unknown, which greatly reduces the amount of computation of the neural network.

Fig.1 itate the description of the structure of the control system, Figure shows the block diagram of the control system designed in this section. (See Figure 1) It can be seen that the main difference between adaptive neural network control and neural network learning control is the update adjustment of neural network weights. In adaptive neural network control, the neural network weight is updated online according to the designed weight update rate, while in the neural network learning control, the stored constant neural network weight is applied to the same or Similar control tasks. By avoiding the tedious and repeated weight parameter adjustment process, the neural network learning controller can achieve better control performance with faster convergence speed and smaller tracking error.

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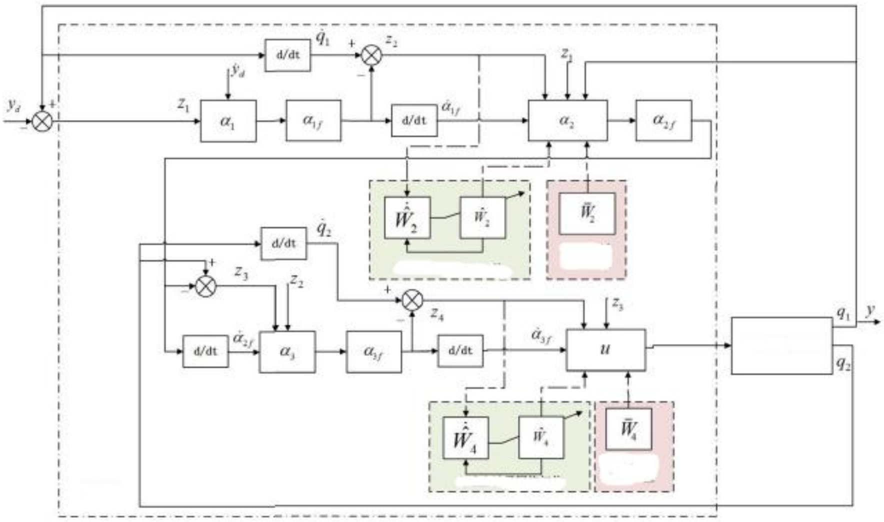

Figure.1 Control System Block Diagram

The control objective is to realize the neural network learning control of the flexible joint manipulator when the measured reference trajectory dynamic mode is unknown. Therefore, a dynamic pattern recognition mechanism needs to be constructed[5], so that the robot arm can monitor and quickly identify the reference trajectory in real time. The dynamic mode also needs to design the controller switching strategy according to the constructed candidate constant value neural network controller group to ensure that the control system can reasonably call the controller to implement accurate trajectory tracking after identifying the reference trajectory dynamic mode.In short, by constructing the RBF neural network to accurately approximate the unknown dynamics of the system, and then to solve the problem of the surge of computational burden of the neural network caused by the system order, the dynamic surface control method is adopted to design the adaptive neural network controller, and the nerve is reduced. The network input dimension and the reduction of the number of neural networks have successfully reduced the computational burden of the control system. According to the determination of the local RBF neural network in the learning theory, under certain conditions, it has the ability to accurately approximate the unknown dynamics of the system. In this section, the controller neural network weights obtained just now are saved in the form of constant values and used to construct new ones. Constant neural network controller. When the neural network learning control system performs the same or similar reference trajectory tracking control, the constant value neural network controller does not need to train and adjust the neural network weight again, so the error convergence speed and tracking accuracy are included. Control performance has been improved. This paper will introduce the design of control system based on dynamic pattern recognition in the next section. By constructing dynamic pattern recognition mechanism, the control system can monitor and identify the reference

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trajectory mode in real time, and design the controller switching strategy based on the constant value neural network controller group. To realize the mode switching control of the control system in a dynamic environment.

6.2 dynamic Pattern Recognition Mechanism

According to the dynamic pattern recognition method mentioned in the learning theory, it is necessary to construct the RBF neural network to the reference track.The unknown dynamics ($f_d^k(x_{d1}^k, x_{d2}^k)$) in the trace mathematical model are approximated. Similar to the construction method of the constant-valued neural network controller group introduced in Chapter 3, the weights in the neural network are saved as empirical knowledge based on the neural network modeling and training results of the system dynamics under different dynamic modes. In order to construct a dynamic pattern library that stores empirical knowledge of different dynamic modes.

The constant value neural network weights used to describe the reference trajectory variation characteristics in different dynamic modes can be obtained by determining the learning theory, and the empirical knowledge representing the different dynamic modes is saved in the dynamic pattern library, and the dynamic pattern library is recorded. According to the definition of similarity, the similarity between patterns can be attributed to the dynamic similarity within the system, but because its internal dynamics cannot be directly obtained[6], it is impossible to directly judge the similarity based on this. According to the dynamic pattern recognition method, it can be known that the state difference between different dynamic modes is approximately proportional to its inherent dynamic difference. When the dynamic mode of the measured reference trajectory is the same as the kth mode in the dynamic mode library, $\bar{x}_e^k$ the residual average L1 norm can be obtained as the decision norm of the detection.

According to the strategy given above, the entire dynamic pattern recognition process is divided into two stages: the pattern pre-identification stage and the pattern recognition. The mode pre-recognition strategy determines whether the current reference trajectory mode changes according to the change of the decision norm corresponding to the current dynamic mode in the time domain, and the pattern recognition strategy is based on the size of each decision norm over a period of time. The relationship determines the dynamic mode category to which the current reference track belongs. Therefore, it is necessary to design a pattern pre-identification strategy, so that the control system can detect the occurrence of this situation in time, and prepare for the tracking performance and stability of the control system in the pattern recognition stage. The controller switching strategy introduced in the second section is It was proposed to deal with such situations.

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6.3 based on Experience Knowledge Controller Group Design Switching

According to the constructed dynamic pattern recognition mechanism, the system can realize the real-time monitoring of the reference trajectory and the rapid recognition of the trajectory mode. In a simple application, that is, when the system only needs to perform one tracking task, the system recognizes the current reference. After the dynamic mode of the track, the corresponding controller in the candidate constant value neural network controller group can be directly invoked to implement the control. However, under normal circumstances, the system may need to continuously execute multiple control tasks during the running time. At this time, there will be several time points for mode switching during the running time. When the dynamic mode of the reference trajectory changes at these points in time, the system can respond in time according to the pattern pre-recognition strategy, and then make corresponding judgments according to the size relationship between the residuals in a given time period. Because the system uses the controller before the mode switchover from the time when the system sends the response to the mode judgment, the current controller will not match the current reference track mode. Causes tracking performance to deteriorate. In order to improve the trajectory tracking problem of the control system in the pattern recognition stage, it is necessary to correct the expression of the controller at this stage.

According to the designed pattern pre-identification strategy and pattern recognition strategy, combined with the dynamic estimator based on the dynamic pattern library design and the constructed candidate constant-value neural network controller group, the flexible joint manipulator is tracked and controlled. In $(t_p^i, t_c^j]$ the controller during this transition period is:

$$u^{i'} = \begin{cases} -z_3^i - C_4^i z_4^i - \bar{W}_4^i S_4^i(\Psi_4^i), \Omega_{\Psi_d^j} \subset \Omega_{\Psi_d^i}, t \in (t_p^i, t_c^j] \\ -z_3^i - C_{4h}^i z_4^i - \bar{W}_4^i S_4^i(\Psi_4^i), \Omega_{\Psi_d^j} \subset \Omega_{\Psi_d^i}, t \in (t_p^i, t_c^j] \end{cases} \quad (12)$$

The correction of the controller according to the above formula is based on the difference between the training fields between the two dynamic modes before and after the switching. Because the local RBF neural network constructed in this paper realizes the dynamic local accurate approximation of the system along the regression trajectory, there are differences in the neural network node distribution and weight matrix between different dynamic modes. When the controller does not match the mode of the reference trajectory, the difference between the training domains will cause the output of the neural network to be unable to cancel the actual system dynamics, thus affecting the tracking performance of the system. In this case, the tracking error of the system will be very large, so that the boundedness of the system signal can not be guaranteed, and the high gain controller given in this paper is the emergency measures taken to suppress the divergence of the tracking error. The short-lived pattern recognition ensures the boundedness of the signal and the finiteness of the system energy during the transition.

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The controller obtained above can ensure the boundedness of the signal in the pattern recognition phase. However, when the system ends the pattern recognition, that is, when the system makes the judgment of the reference trajectory dynamic mode, the controller will switch at this moment. . Since the parameters and structure of the controller before and after switching are different, it is likely that the control signal is not smooth and continuous at the switching time, which affects the stability of the control system. Therefore, the controller switching strategy needs to be further designed. The controller switching strategy is similar to the proof analysis of the theorem in the third section.It is also possible to $(t_p^i, t_c^j]$ demonstrate the uniform boundedness of all signals in the closed-loop control system of the manipulator and the convergence of the system state tracking error over time. In summary, in the dynamic mode closed-loop control system, all signals in the entire pattern recognition process are finally uniformly bounded, and the system state tracking error will converge into the neighborhood of zero.

7. Conclusion

In this study, the trajectory tracking control problem of the flexible joint manipulator with performance constraints is discussed. Based on the characteristics of the performance-limited control method, in the follow-up work, how to control the performance-limited control ideas based on Dynamic pattern recognition controls are combined to further improve the control scheme.According to the given pattern recognition and control scheme, the control simulation results of the two-link flexible joint manipulator are demonstrated. It is verified that the scheme can not only realize the real-time monitoring of the dynamic mode of the robot arm system without human intervention. Autonomous fast identification, and can ensure the stability of the control arm during the mode switching process, and improve the transient performance of the system controller switching process.

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