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The neural network sliding mode controller based on multiple model for Robotic Manipulators

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Abstract. A Multi-model neural network sliding mode controller (MNNSMC) is proposed for robotic manipulator in this paper. The proposed MNNSMC scheme combining the SMC (sliding mode control) and neural network technique. The multi-model ensures that when the working environments of robotic manipulator are changeful, we can choose the proper model to get better control indicators. The controller applies the SMC to obtain high response and invariability to uncertainties and adopts neural network to estimate the switch gain in order to weaken the sliding mode chattering. The neural network is trained extensively with the state estimation error backpropagation learning algorithm. It consists of an input layer, hidden layer and output layer. Input layer of vector are errors and velocity errors and output layer of vector means to estimate the switch gain. In order to ensure the rationality of the switch, a new switching index is proposed which is a PID type with forgetting factor. The simulation results demonstrate the effectiveness and feasibility of the proposed control strategy.

Introduction

Controllers for nonlinear, time-varying and coupled mechanical system, such as robotic manipulator system, are widely studied in order to improve system performance. However, the working environments of robotic manipulator are changeful; there exist external disturbances, parameter variations and uncertainties, which cannot be predicted usually. Therefore, it is very important to design a good controller to improve the control quality. Various nonlinear control methods have been proposed for solving this problem, including SMC, neural network, etc.

Because of its strong anti-interference ability and robust performance in nonlinearities, sliding mode control is widely researched. In general, SMC is a special kind of nonlinear control due to its discontinuous control input which drives the control system toward a specified sliding surface according to the current state of the system (such as the deviation and its derivative, etc). SMC is not sensitive to parameter change and disturbances because the sliding surface can be designed independently and has nothing to do with system parameters. In recent years, more and more sliding mode control was applied to the trajectory control of robotic manipulator. Many scholars researched and developed the sliding mode control,such as fuzzy sliding mode control[1-4], neural network sliding mode control[5,6], dynamic sliding mode control[7], terminal sliding mode control[8,9], backstepping sliding mode control, etc.

Although classical SMC is a powerful scheme for nonlinear systems with uncertainties,SMC still has its drawbacks. Due to contain a discontinuous function, when the states reached the sliding mode surface, it is difficult to slide with the sliding mode surface, but crossing back and forth on both sides of it resulting in a sliding mode chattering. Many scholars put forward different solutions to solve the problem of the sliding mode chattering, such as saturation function method, reaching law method, filter method, etc.

Theorem

According to the Euler-Lagrangian formulation,the equation of a multi degrees of freedom (DOF) robot manipulator is calculated by the following equation [10]:

$$\begin{aligned} &\boldsymbol{M\ddot{q}} + \boldsymbol{C\dot{q}} + \boldsymbol{G} = \boldsymbol{\tau} + \boldsymbol{f} \\ &\boldsymbol{y} = \boldsymbol{q} \end{aligned} \tag{1}$$

Where $\boldsymbol{M} = \boldsymbol{M(q)}$ is symmetric and positive define inertia matrix, $\boldsymbol{C} = \boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})$ is Coriolis and centrifugal forces vector. $\boldsymbol{G} = \boldsymbol{G}(\boldsymbol{q})$ is the vector resulting from the gravitational forces, $\boldsymbol{f}$ is the vector containing the unmodeled dynamics and the uncertainties. $\boldsymbol{q} = [q_1 \cdots q_n]^{\mathrm{T}}$ is position vector.

The control objective is to force $\boldsymbol{q} = [q_1 \cdots q_n]^{\mathrm{T}}$ in the system (1) to track a bounded desired trajectory $\boldsymbol{q_d} = [q_{1d} \cdots q_{nd}]^{\mathrm{T}}$,under the constraint that all variables involved must be bounded.

Neural Network Sliding Mode Controller Design

Let the tracking error be defined as $\overline{\boldsymbol{e}} = \boldsymbol{y} - \boldsymbol{y_d} = [\boldsymbol{e},\dot{\boldsymbol{e}}]^T$, and a sliding mode surface be defined as $\boldsymbol{s} = k_1\boldsymbol{e} + \dot{\boldsymbol{e}} = k^T\overline{\boldsymbol{e}}$, where $k = [k_1,1]^T$ are the coefficients of the Hurwitz polynomial $h(\lambda) = \lambda + k_1$. If the initial error vector $\boldsymbol{e}_0 = 0$, then the tracking problem can be considered as the state error vector $\overline{\boldsymbol{e}} = \boldsymbol{y} - \boldsymbol{y_d} = [\boldsymbol{e},\dot{\boldsymbol{e}}]^T$ remaining on the sliding mode surface $s = 0$ for all $t > t_0$.

A sufficient condition to achieve this behavior is to select a control strategy such that:

$$\frac{1}{2}\frac{d}{dt}(s^2) \le -\eta|s|, \eta > 0 \tag{2}$$

From (2), we have

$$\begin{aligned} \dot{\boldsymbol{s}} &= k_1\dot{\boldsymbol{e}} + \ddot{\boldsymbol{y}} - \ddot{\boldsymbol{y}}_d \\ &= k_1\dot{\boldsymbol{e}} + \boldsymbol{M}^{-1}\tau - \boldsymbol{M}^{-1}C\dot{\boldsymbol{q}} - \boldsymbol{M}^{-1}G + \boldsymbol{M}^{-1}\boldsymbol{f} - \ddot{\boldsymbol{y}}_d \end{aligned} \tag{3}$$

If $\boldsymbol{M}^{-1}, \boldsymbol{C}$ and $\boldsymbol{G}$ are known, we can easily construct the sliding mode control $\boldsymbol{u}^* = \boldsymbol{u}_{eq} - \boldsymbol{u}_{sw}$,

$$\boldsymbol{u}_{eq} = \text{-}k_1\boldsymbol{M\dot{q}} + \boldsymbol{C\dot{q}} + \boldsymbol{G} + k_1\boldsymbol{M\dot{q}}_d + \boldsymbol{M\dot{q}}_d \tag{4}$$

$$\boldsymbol{u}_{sw} = \boldsymbol{M}\eta\,\mathrm{sgn}(s) \tag{5}$$

However, power system parameters are not well known and imprecise, therefore it is difficult to implement the control law for unknown nonlinear system model. Not only $\boldsymbol{M}^{-1}, \boldsymbol{C}$ and $\boldsymbol{G}$ have unknown parts but the switching-type control term will cause chattering. A neural network sliding mode controller is proposed to solve these problems. Neural network technology is used to realize the unknown parts soft measurement.

A typical three layer feedforward NN is given in figure 1.

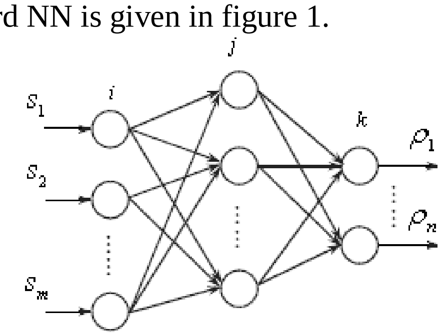

Fig.1 The topology of the three-layer neural network

The output of Hidden node j is given by: $H_j = \sigma(z_j)$

where, $z_j = \sum_i V_{ji} x_i + \mu_j$, v_{ji} is the weight between input node i and the hidden node j , μ_j is a threshold of the hidden node j . The output of output node k is

$$\rho_{\boldsymbol{k}} = \sum_j W_{kj} H_j \tag{6}$$

where, W_{kj} is the weight between hidden node j and output node k . $\sigma(.)$ is a sigmoidal function. There are many forms of this function. But,we design the sigmoid function this form:

$$\sigma(Vz) = \frac{2}{1+\exp[-(2\sum_j V_{ji} s_i)]} - 1 \tag{7}$$

and $\boldsymbol{\rho} = \boldsymbol{W}\sigma(Vz) + \varepsilon(t),\ \varepsilon(t) \le \varepsilon_{\max}$, $\varepsilon(t)$ is neural network modeling error. Neural network adaptive law is designed as follows,see literature [11] ,

$$\begin{aligned} \dot{\hat{\boldsymbol{W}}} &= F_1 \boldsymbol{e} (\sigma_1(\hat{\boldsymbol{V}}\hat{z}))^{\mathrm{T}} - kF_1 \| \boldsymbol{e} \| \hat{\boldsymbol{W}} \\ \dot{\hat{\boldsymbol{V}}} &= (\hat{\boldsymbol{W}}\sigma_2(\hat{V}\hat{z}))^{\mathrm{T}} F_2 \boldsymbol{e}\hat{z} - kF_2 \| \boldsymbol{e} \| \hat{\boldsymbol{V}} \end{aligned} \tag{8}$$

Where, $z = [s\ \boldsymbol{x}_d]^{\mathrm{T}}$, $\hat{W}\sigma(\hat{\boldsymbol{x}}, \boldsymbol{x}_d)$ is the estimator of $\boldsymbol{\rho}$, $F_i = F_i^{\mathrm{T}} > 0$, $\kappa_i > 0$, $i = 1, 2$, $\sigma_1(\hat{V}\hat{z}) = \sigma(\hat{V}\hat{z})$, $\sigma_2(\hat{V}\hat{z}) = \sigma(\hat{V}\hat{z})(1 - \sigma(\hat{V}\hat{z}))$.

Multiple Model Control

Multi-model control mechanism is time detection system of performance indicators, to choose a more suitable model of the current environment, and create a more appropriate control signal. So the multi-model control part can be divided into two parts, detection and control.

Detection part of multi-model control

Detection part is composed of predefined multiple model and switching mechanism. The establishment of the multiple models is generally based on the controlled object in the different work enviroments(such as temperature changes, external disturbance and other factors). Switching mechanism is used to decide which one model is more suitable for the current controlled object, and switch to that model. There are many kinds of performance index function is used as the standard switch. We choose the PID performance index with forgetting factor based on the literatures[12,13],and do some modifications increasing weighting factors and forgetting factors, which make the performance index more real-time.

The performance index is selected as

$$J_i(t) = h_1 e_i(t) + h_2 \int_0^t e^{-\kappa(t-\tau)} e_i(\tau) d\tau + h_3 \frac{de_i(t)}{dt} \tag{9}$$

where $e_i(t) = y(t) - \hat{y}_i(t)$, $h_1 > 0$, $h_2 > 0$, $h_3 > 0$, κ is forgetting factor. The weights are used to balance the relationship of the system errors and the transient errors in a long time. Forgetting factor is used to reduce the influence of the old datas gradually.

Control

In the multiple models approach, as shown in fig1, N separated controllers are designed for predefined models which have the same equivalent control $u_{eq1} \cdots u_{eqn}$ and different controller gain $\gamma_1 \cdots \gamma_n$. so the control objective is satisfied for each of them. When performance index function detected some time minimum output error, select the error of the model.

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Simulation

To verify the performance of the proposed Multi-model neural network sliding mode controller, simulation studies have been carried out by MATLAB. Using two joint manipulator system as the simulation object, the dynamic model are as follows [14],

$$\begin{bmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{bmatrix}\begin{bmatrix} \ddot{q}_1 \\ \ddot{q}_2 \end{bmatrix}+\begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix}\begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix}+\begin{bmatrix} G_1 \\ G_2 \end{bmatrix}=\begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix}+\begin{bmatrix} f_1 \\ f_2 \end{bmatrix}$$

where m_1 and m_2 are the masses, L_1 and L_2 are the lengths of the links 1 and 2, τ_1 and τ_2 are applied joint torques (control inputs),and J_1 and J_2 are rotational inertias.

We used the three models in simulation test, system parameters are shown in table 1 and the controller parameters are shown in table 2. Figure 2 is the trajectory tracking chart, we can see the joints can track the designed trajectorys quickly from it, even more strong random disturbance existed.

Table 1. Parameters of Two- Link Robot

Model	m_1	m_2	g	l_1	l_2	r_1	r_2
Model 1	0.77	0.77	9.8	0.25	0.25	0.15	0.15
Model 2	0.9	0.8	9.8	0.3	0.3	0.2	0.2
Model 3	1.0	0.8	9.8	0.4	0.4	0.25	0.25

Table 2.The parameters of controller

Controllers	γ_i	k	κ, h_1, h_2, h_3
Controller 1	2	[30,1]T	6,5,5,3
Controller 2	5	[50,1]T	6,5,5,3
Controller 3	8	[65,1]T	6,5,5,3

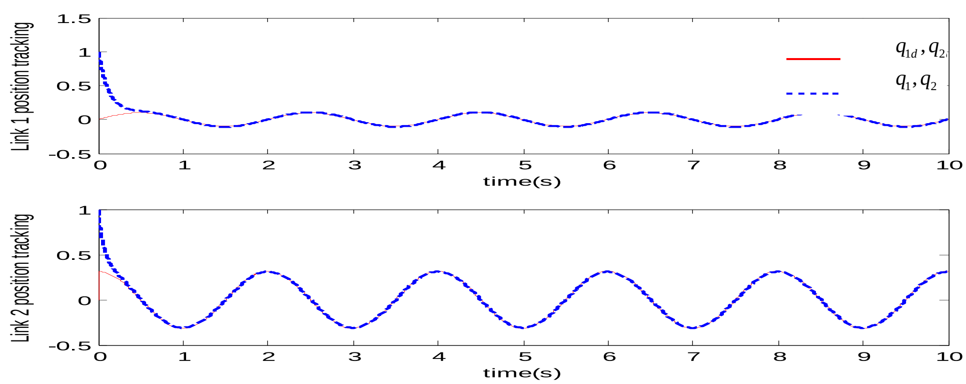

Fig. 2 Desired and actual trajectory for joint 1 and 2

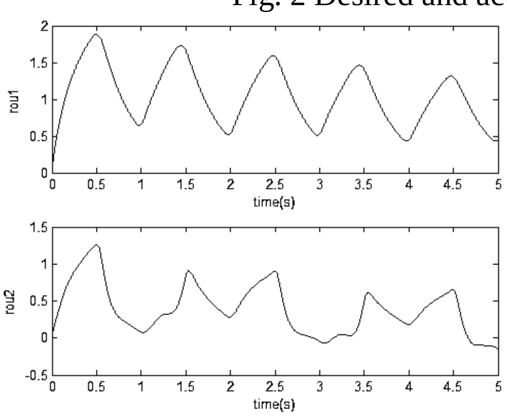

Fig. 3 The output of the neural network

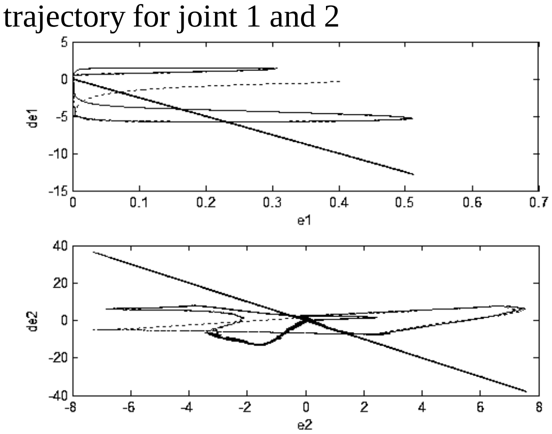

Fig. 4 The phase locus

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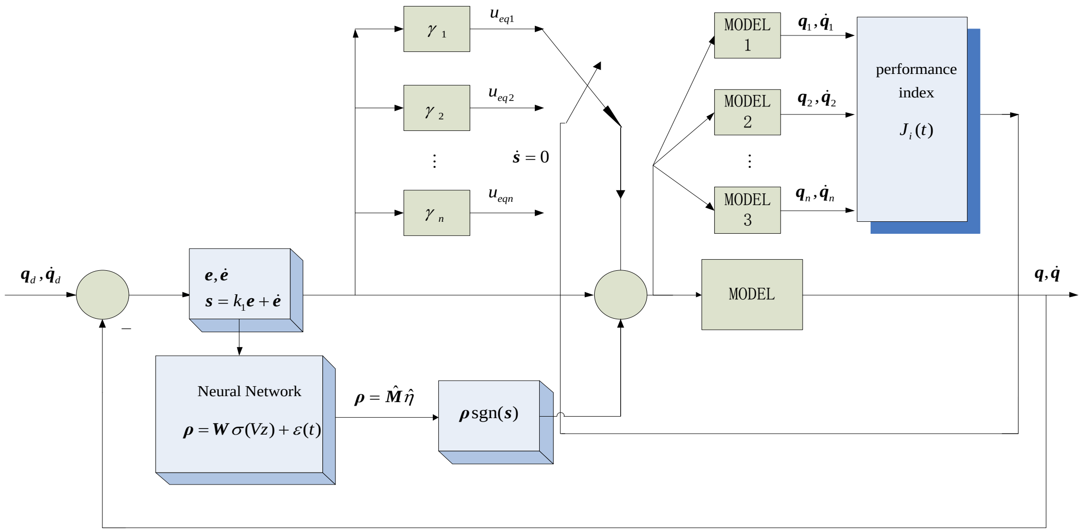

Fig. 5 Block diagram of Multi-model neural network sliding mode control

CONCLUSIONS

A new approach to the design of a Multi-model neural network sliding mode controller which can solve the impacts of different working conditions on the system model is presented. The Multi-model neural network sliding mode controller integrates the sliding mode control strategy and neural network methodology.The combined scheme is shown to have the merits of the sliding mode and the neural network approaches.The use of two rigid robot joints design of robot model inversion is proved by the sliding mode controller is effective and feasible.It is seen from Figure2 that under the functioning of the Multi-model neural network sliding mode controller controller, the robotic manipulator has accurate tracking trajectorys.

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