

A CONTROL METHOD FOR NONLINEAR SYSTEMS USING SLIDING MODE CONTROL COMBINED WITH RBF NEURAL NETWORK

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SUMMARY

In industrial systems, the SISO system in particular and the systems in general are uncertain nonlinear systems with the effects of external disturbance factors. The uncertainty of the system and external disturbances are always changeable, which can not be measured, they would be a major obstacle for linear control method. This paper proposes a method to evaluate the uncertainty and disturbance in the system by using *Radial Basis Function* (RBF) neural network and builds Sliding mode control algorithm for nonlinear systems to ensure sustainable stability against disturbances. Obtained Sliding Mode Control algorithms and weights update rules for the Network, ensuring exist and stability Sliding Mode system. Through illustrative examples Matlab Simulink, simulation confirmed efficiency and ability of the proposed algorithm.

Key word: *SISO system, sliding mode control, robust adaptive control, estimative algorithm for disturbance, RBF neural network.*

INTRODUCTION

Nowadays, most of industrial systems are the uncertain nonlinear systems affected by the external disturbances. The utilization of the conventional controllers such as PID to control this mentioned complex objects normally does not guarantee the stability of system, in fact, the quality requirements of control keeps increasing dramatically. Therefore, the construction of intelligent control that ensures the high precision, robustness with the real disturbances is urgently needed. One of the most effective approaching of control algorithm is the sliding mode control (SMC) based on the selection of sliding modes according to the sliding functions S [1].

The sliding mode controller applied to the current nonlinear systems is usually associated with Neural network [2, 4]. The selection of function of the sliding surface S , the assurance of the sliding modes as well as the reduction of shake phenomenon “chattering” during the manipulation process is always complex and difficult problem that

requires the careful consideration of the designers [3]. The Neural network can be used for the estimation of the effects of external disturbances to the system and approximation of uncertain components of the object thereby compensating those impacts on the system by compensating the control signals.

The following proposes the new control method for nonlinear SISO system in which applies the Neural RBF network to approximate the uncertain components, then updating the system control law with respect to the adjustment of the uncertain parts based on the sliding mode in order to ensure the robust stability of the system.

THE SYNTHESIS OF SLIDING MODE CONTROL BASED ON UNCERTAIN COMPONENTS ESTIMATION BY THE NEURAL RBF NETWORK FOR THE NONLINEAR SISO SYSTEM

Constructing the sliding mode controller for the nonlinear SISO system

Considering the second order nonlinear system as following form:

$$\ddot{\theta} = g(\theta, \dot{\theta}).u + f(\theta, \dot{\theta}) + d(t) \quad (1)$$

where:

$g(\cdot), f(\cdot)$: the uncertain function of the system

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$u \in \mathbb{R}$: the output signal of controller

θ : the output signal of the object

$|d(t)| \in \mathbb{R}$: the external disturbance affecting the system.

The given problem is designing the sliding mode control that ensuring the output control of the θ object following the reference signal θ_d , with the error $e = \theta_d - \theta$.

Supposing that the sliding surface S is selected as:

$$\dot{S} = \dot{e} + ce = 0 \quad (2)$$

when $c > 0$:

$$\begin{aligned} \dot{S} &= \ddot{e} + c\dot{e} = \ddot{\theta}_d - \ddot{\theta} + c\dot{e} = \\ &= \ddot{\theta}_d - f - gu - d(t) + c\dot{e} \end{aligned} \quad (3)$$

Therefore, if the functions $f(\cdot)$ and $g(\cdot)$ are determined, the control law will be formed as:

$$u = \frac{1}{g} [-f + \ddot{\theta}_d + c\dot{e} + \mathbf{A} \text{sign}(S)] \quad (4)$$

where: $\mathbf{A} \text{sign}(S)$ - The Relay component with border matrix is \mathbf{A} . Where matrix \mathbf{A} was chosen: $\mathbf{A}^3 \mathbf{D}$ to guarantee that the operating point always be drawn on the sliding surface when it reaches the sliding surface (called Chattering phenomenon) \mathbf{D} is border of disturbance affecting the system, depend on each plant.

Then:

$$\dot{S} = \ddot{e} + c\dot{e} = -\mathbf{A} \text{sign}(S) - d(t)$$

If $\mathbf{A}^3 \mathbf{D}$, we have:

$$\mathbf{S} \dot{S} = -\mathbf{A} |S| - \mathbf{S} d(t) \leq 0$$

Assuming that the given problem set the component $f(\cdot)$ is unknown, it is needed to choose the algorithm to estimate $f(\cdot)$. Therefore, this paper presents the use of Neural network RBF to approximate the component $f(\cdot)$.

Selecting the algorithm for uncertain component estimation by the Neural RBF network for the nonlinear SISO system [4]

To approximate the uncertain component in the nonlinear SISO system, the Neural RBF network is employed with the fundamental function \mathbf{h} :

$$\mathbf{h} = \exp \left(\frac{\|\mathbf{x} - c_{ij}\|^2}{2b_j^2} \right) \quad (5)$$

$$f = \mathbf{W}^{*T} \mathbf{h} + \varepsilon \quad (6)$$

Where: \mathbf{x} is the input signal of Neural network; i is the number of inputs of Neural network; j is the number of fundamental function of the invisible class in the network; c_{ij} is centre of basic function, b_j is the extent of the basis function; $\mathbf{h} = [h_j]^T$ is the output of the Gaussian function; \mathbf{W}^* is the ideal weight function of Neural network; ε is the approximately error of Neural network; $f(\cdot)$ is the network output.

In this paper, the input of network is selected as: $\mathbf{x} = [e \ \dot{e}]^T$, and the output of the RBF network is:

$$\hat{f} = \hat{\mathbf{W}}^T \mathbf{h} \quad (7)$$

Then, the control signal is:

$$u = \frac{1}{g} [-\hat{f} + \ddot{\theta}_d + c\dot{e} + \mathbf{A} \text{sign}(S)] \quad (8)$$

And:

$$\begin{aligned} \dot{S} &= \ddot{\theta}_d - f - gu - d(t) + c\dot{e} = \\ &= \ddot{\theta}_d - f - [-\hat{f} + \ddot{\theta}_d + c\dot{e} + \mathbf{A} \text{sign}(S)] - d(t) + c\dot{e} \\ &= -f + \hat{f} - \mathbf{A} \text{sign}(S) - d(t) \\ &= -\tilde{f} - d(t) - \mathbf{A} \text{sign}(S) \end{aligned} \quad (9)$$

$$\text{where: } \tilde{f} = f - \hat{f} = \mathbf{W}^{*T} \mathbf{h} + \varepsilon - \hat{\mathbf{W}}^T \mathbf{h}$$

$$= \tilde{\mathbf{W}}^T \mathbf{h} + \varepsilon \quad (10)$$

$$\text{while: } \tilde{\mathbf{W}} = \mathbf{W}^* - \hat{\mathbf{W}}$$

To ensure the existence of the convergence of the sliding modes and estimate algorithm of uncertain component, it is necessary to determine the sufficient condition based on the selection of Lyapunov function:

$$\mathbf{V} = \frac{1}{2}\mathbf{S}^2 + \frac{1}{2}\gamma\tilde{\mathbf{W}}^T\tilde{\mathbf{W}} \text{ với } \gamma > 0$$

We have:

$$\begin{aligned} \dot{\mathbf{V}} &= \mathbf{S}\dot{\mathbf{S}} + \gamma\tilde{\mathbf{W}}^T\dot{\tilde{\mathbf{W}}} \\ &= -\tilde{\mathbf{W}}^T(\mathbf{S}h + \gamma\dot{\tilde{\mathbf{W}}}) - \mathbf{S}(\varepsilon + d(t) + \text{Assign}(\mathbf{S})) \end{aligned}$$

If $\dot{\tilde{\mathbf{W}}} = -\frac{1}{\gamma}\mathbf{S}h$ then:

$$\dot{\mathbf{V}} = -\mathbf{S}(\varepsilon + d(t) + \text{Assign}(\mathbf{S})) \leq 0 \quad (*)$$

where $\mathbf{A}^3 \varepsilon_M + \mathbf{D}$

Thus, from (*), it is clearly shown that the algorithm is always converged and the existence condition is continuously guaranteed.

Applying the control law and proposed identified algorithm to the nonlinear SISO objects

Considering the dynamics of inversed pendulum equation as following:

$$\begin{aligned} \ddot{\theta} &= f(.) + g(.)u + d(.) \\ &= \frac{g \sin \theta - ml\dot{\theta}^2 \cos \theta \sin \theta / (m_c + m)}{l(4/3 - m \cos^2 \theta / (m_c + m))} + \\ &\quad \frac{\cos \theta / (m_c + m)}{l(4/3 - m \cos^2 \theta / (m_c + m))} u + 0,1 \sin(0,5t) \end{aligned}$$

where:

θ : the rotated angle of the inverse pendulum

$\dot{\theta}$: the angle velocity of the inverse pendulum

$\ddot{\theta}$: the angle acceleration of the inverse pendulum

$g = 9.8m/s^2$: the gravity acceleration

$m_c = 1kg$: the mass of the pendulum

$m = 0.1kg$: the mass of the bar

$l = 0.5m$: a half-length of the bar

u : the control signal of the motor that rotates the pendulum bar.

+ The structure of the selected Neural RBF network is the first order invisible class with two inputs; five invisible Neural classes and one output as presented in Figure. 1.

+ The simulation parameters:

$$\theta_d = 0.1 \sin(t)$$

$$c = 15; \mathbf{A} = 0.1; \gamma = 0.05$$

$$c_{ij} = [-1 \ 0.5 \ 0 \ 0.5 \ 1]; b_i = 0.5$$

$$d(t) = 0,1 \sin(0,5t)$$

It should be noted that the dynamic equation of inversed pendulum always implies the uncertainty in the components $f(.)$, $g(.)$ when any disturbance component affects the system.

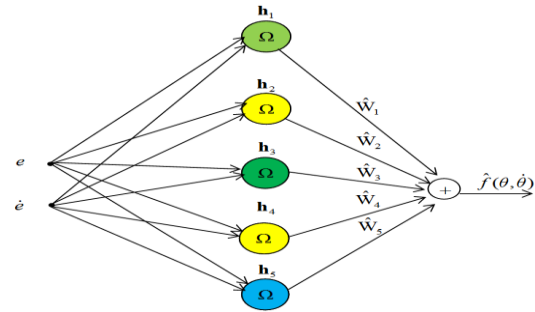


Figure 1. The structure of Neural RBF

Simulation Results

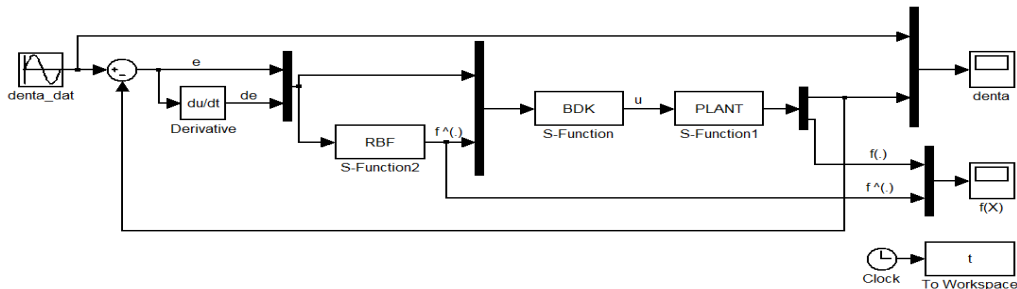


Figure 2. The control structure of the inverse pendulum using Sliding mode controller based on uncertainty identification $f(.)$

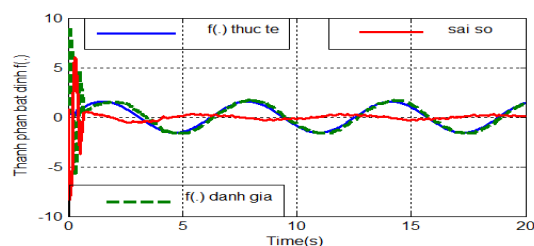


Figure 3. The estimation of the uncertain component by the Neural RBF network

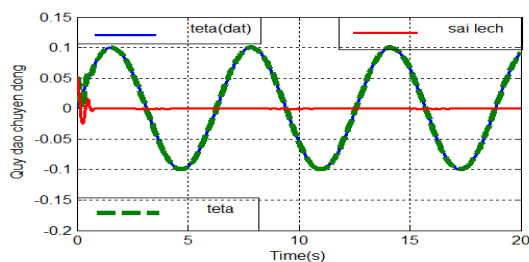


Figure 4. The motion of the inverse pendulum

Based on the identification algorithm for the uncertain component $f(\cdot)$, we construct the sliding mode control law simulated in Matlab-Simulink as shown in Figure 2. The control structure of the inverse pendulum using Sliding mode controller based on uncertainty identification $f(\cdot)$ is presented in Figure 2. The estimation of the uncertain component by the Neural RBF network is shown in Figure 3. Combining the Sliding mode controller based on disturbance estimation employing the Neural RBF network, the motion of the inverse pendulum is described as shown in Figure 4.

Remarks

The results of identification of uncertain components $f(\cdot)$ as shown in Figure. 3 and the motion of the inverse pendulum is following the reference in Figure. 4 confirm the efficiency of the identified algorithm and the proposed control law ensuring the convergence in identification and estimation of the uncertainties with allowable error and allowing the stability of the motion of the inverse pendulum with the uncertain parameters of the system.

CONCLUSION

This paper proposed a control method for the nonlinear system employing the sliding mode control combined with the Neural RBF network. The sliding mode control algorithm and the weight updating law for the network are achieved to guarantee the existence of sliding mode and stability for the system. The efficiency of the proposed algorithms are confirmed by an example and the simulation in Matlab - Simulink.

LỜI CẢM ƠN

Kết quả nghiên cứu của bài báo được thực hiện bởi kinh phí do trường Đại học Kỹ thuật Công nghiệp cấp cho đề tài KH&CN: Một phương pháp điều khiển cho hệ phi tuyến sử dụng bộ điều khiển Sliding mode kết hợp với mạng Neural RBF.

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TÓM TẮT**MỘT PHƯƠNG PHÁP ĐIỀU KHIỂN CHO HỆ PHI TUYẾN SỬ DỤNG
BỘ ĐIỀU KHIỂN SLIDING MODE KẾT HỢP VỚI MẠNG NEURAL RBF****Lê Thị Huyền Linh^{*}, Trần Thị Thanh Hải***Trường Đại học Kỹ thuật Công nghiệp – ĐH Thái Nguyên*

Trong các hệ thống công nghiệp, hệ SISO nói riêng và các hệ thống nói chung đều có tính chất phi tuyến bất định với sự ảnh hưởng của các yếu tố nhiễu bên ngoài tác động. Sự bất định của hệ thống và nhiễu bên ngoài luôn thay đổi, có thể không đo được, nên sẽ là sự cản trở lớn đối với các phương pháp điều khiển tuyến tính. Vì vậy bài báo đề xuất một phương pháp để đánh giá sự bất định và nhiễu trong hệ thống thông qua mạng Neural RBF, đồng thời xây dựng thuật toán điều khiển Sliding mode cho hệ phi tuyến đảm bảo tính ổn định bền vững kháng nhiễu tốt. Đã thu được thuật toán điều khiển trượt và luật cập nhật trọng số cho mạng, đảm bảo tồn tại chế độ trượt và ổn định cho hệ thống. Thông qua ví dụ minh họa mô phỏng trên Matlab Simulink khẳng định được tính hiệu quả và khả thi của các thuật toán đề xuất.

Từ khoá: *Hệ SISO, Điều khiển Sliding Mode, Điều khiển thích nghi bền vững, Thuật toán đánh giá nhiễu, mạng neural RBF.*

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