



New Design of Neuro - Sliding Mode Control With Chattering Elimination For Twin Rotor MIMO System (TRMS)

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Abstract—In this paper, we will propose a cooperative control approach that is based on the combination of neural network (NN) and the methodology of sliding mode control (SMC) for a twin rotor multi-input multi- output system(TRMS). The TRMS is an experimental aerodynamic test bed representing the control challenges of unmanned aerial vehicles. The main purpose is to overcome the problem of the equivalent control computation and to eliminate the chattering phenomenon. A feed forward neural network (NN) with the learning rule based on sliding mode algorithm is used to assure the calculation of the equivalent control in the presence of plant uncertainties. The weights of the net are updated such that the corrective control term of Neurosliding mode control goes to zero. Simulation results show that the proposed design can successfully adapt to system nonlinearity and complex coupling conditions. It is shown that the proposed control is feasible and effective.

Index Terms-neural networks, Sliding mode, Twin Rotor MIMO System

I. INTRODUCTION

Sliding mode control (SMC) is particular type of variable structure control system that is designed to drive and then constrain the system to lie within a neighborhood of the switching function which is a nonlinear control strategy that is well known for its robustness .The essential characteristic of SMC is that the feedback signal is discontinuous, switching on one or more manifolds in state space. When the state crosses each discontinuity surface, the structure of the feedback system is altered. All motion in the neighborhood of the manifold is directed toward the manifold. When the system states stay in the sliding surface, the equivalent control is capable of making the system stay in the surface. The SMC suffers two main disadvantages [1]. The first one is that there always exists high frequency oscillation in the control input, which is called "chattering". The second disadvantage is that it is difficult to obtain parameters of the system. The equivalent control cannot be calculated because the system parameters are unknown. The most popular technique for the elimination of chattering is to adopt a saturation function [3] or other methods [4]–[6]. In order to avoid the computational burden, we use an estimation technique to calculate the value of equivalent control. The intelligent computational techniques have beenutilized to control problems for many years. Among them neural networks [1], fuzzy systems [2] and genetic algorithms [3] are the most popular approaches. The Neural networks have been widely applied for state feedback controller design, nonlinear system control, nonlinear dynamical system identification, and optimal control synthesis. Although the neural networks have many benefits, the disadvantage of the neural networks is that the training process is time consuming [4]. Thus, simple neural network structure is needed, especially for real-time control system.

In recent years, much attention has been paid to neural network based controllers .The nonlinear mapping and learning properties of neural networks (NNs) are key factors for their use in the control field. In general, a neural network controller with the learning rule based on sliding mode algorithm, is used to assure calculation of unknown part of the equivalent control in the presence of plant uncertainties. And, this controller possesses the features of robustness under parameter variation and external disturbance. Moreover, the controller comprises of two parts: the first one is a neural network based equivalent control calculation with its learning rule determined from sliding mode design [5], and the second one is a sliding mode based chattering-free SMC [6]. In this way the properties of the neural network and SMC are combined to provide good dynamical responses even in the cases while limited knowledge on the system is available. The learning rule is based on sliding mode design and can assure fast neural network convergence without any off-line training. This paper proposes a neural network controller to compute the equivalent control and also this (NN) alleviates the chattering phenomenon because a big gain in the corrective control term produces a more serious chattering than a small gain. The weights of the neural network are updated such that the corrective control term of Neuro-sliding mode control goes to zero.

This paper is organized as follows. Section II presents the twin rotor multi-input multi-output system model and brief





introduction of the TRMS system. Section III describing the methodology of NNs based sliding mode control. In section IV presents simulations results, followed by some concluding remarks in section V.

II. TWIN ROTOR MIMO SYSTEM

The TRMS, as shown in Fig. 1, is characterized by complex, highly nonlinear and inaccessibility of some states and outputs for measurements, and hence can be considered as a challenging engineering problem [7]. The control objective is to make the beam of the TRMS move quickly and accurately to the desired attitudes, both the pitch angle and the azimuth angle. The TRMS is a laboratory set-up for control experiment and is driven by two DC motors. Its two propellers are perpendicular to each other and joined by a beam pivoted on its base that can rotate freely on the horizontal plane and vertical plane. The joined beam can be moved by changing the input voltage to control the rotational speed of these two propellers. There is a Pendulum Counter-Weight hanging on the joined beam which is used for balancing the angular momentum in steady state or with load. In certain aspects its behavior resemblesthat of a helicopter. It is difficult to design a suitable controller because of the influence between two axes and nonlinear movement. From the control point of view it exemplifies a high order nonlinear system with significant cross coupling.



Fig. 1. Twin rotor multi-input multi-output system.

A block diagram of the TRMS model is shown in Fig. 2, where M_v is the vertical tuning moment, j_v is the moment of inertia with respect to horizontal axis, α_v is the vertical position (pitch position) of TRMS beam, l_m is the arm of aerodynamic force from main rotor, l_t is the effective arm of aerodynamic force from tail rotor, g is the acceleration of gravity, ω_m is the rotational speed of main rotor, $F_{\nu}(\omega_m)$ is the nonlinear function of aerodynamic force from main rotor, k_{μ} is the moment of friction force in horizontal axis, Ω_{μ} is the angular velocity (pitch velocity) of TRMS beam, his the angular velocity (azimuth velocity) of TRMS beam, α_{h} is the horizontal position (azimuth velocity) of TRMS beam, M_h is the horizontal turning torque, j_h is the nonlinear function of moment of inertia with respect to vertical axis, ω_t is the rotational speed of tail speed, $F_h(\omega_t)$ is the nonlinear function of aerodynamic force from tail rotor, k_h is the moment of friction force in horizontal axis, j_{tr} is the vertical angular momentum from tail rotor, j_{mr} is the vertical angular momentum from main rotor, s_v is the vertical turning moment, s_h is the horizontal turning moment, S_f is the balance factor, U_v and U_h are the DC-motor control inputs. In order to control TRMS on the vertical plane and horizontal plane separately, the main rotor and tail rotor are decoupled.



Fig. 2. Block diagram of the TRMS model.



Fig. 3. Block diagram of the two propellers.

The mathematical model of main rotor is shown below

$$\frac{dS_{\nu}}{dt} = l_m F_{\nu}(\check{S}_m) - \Omega_{\nu} k_{\nu} + g((A - B) \cos r_{\nu} - C \sin r_{\nu}) - \frac{1}{2} \Omega_h^2 (A + B + C) \sin 2r_{\nu}$$
(1)

$$\frac{d\Gamma_{v}}{dt} = \Omega_{v} \tag{2}$$



(5)



$$\Omega_v = \frac{S_v + J_{tr} \check{S}_t}{I}$$

$$\frac{du_{vv}}{dt} = \frac{1}{T_{mr}} (-u_{vv} + K_{mr} u_{v})$$

$$\check{S}_m = P_v(u)$$

Where

$$\begin{cases} A = \left(\frac{m_t}{2} + m_{tr} + m_{ts}\right) l_t \\ B = \left(\frac{m_m}{2} + m_{mr} + m_{ms}\right) l_t \\ C = \left(\frac{m_b}{2} l_b + m_{cb} l_{cb}\right) \end{cases}$$

_{vv})

 m_{mr} is the mass of the main DC motor with main rotor, m_m is the mass of main part of the beam, m_{tr} is the mass of tail motor with tail rotor, m_t is the mass of the tail part of the beam, m_{cb} is the mass of the counter-weight, m_b is the mass of the counter-weight beam, m_{ms} is the mass of the main shield, m_{ts} is the mass of the tail shield, l_b is the length of counter-weight beam, l_{cb} is the distance between the counter-weight and the joint.

Assume the main rotor is an independent system, then (1) to (5) can be written as:

$$\frac{dS_{\nu}}{dt} = l_m F_{\nu}(\tilde{S}_m) - \Omega_{\nu} k_{\nu} + g((A - B)\cos r_{\nu} - C\sin r_{\nu}) \quad (6)$$

$$\frac{d\mathbf{r}_{v}}{dt} = \mathbf{\Omega}_{v} \tag{7}$$

$$\Omega_{\nu} = \frac{s_{\nu}}{j_{\nu}} \tag{8}$$

$$\frac{du_{vv}}{dt} = \frac{1}{T_{mr}} (-u_{vv} + K_{mr} u_v)$$
(9)

$$\check{\mathsf{S}}_m = P_v(u_{vv}) \tag{10}$$

Block diagram of main rotor is shown in Fig. 4.



Fig. 4. Block diagram of main rotor.

(3) The mathematical model of tail rotor is shown below

$$\frac{dS_h}{dt} = l_t F_h(\check{S}_t) \cos \Gamma_v - \Omega_h k_h \tag{11}$$

$$\frac{d\Gamma_h}{dt} = \Omega_h \tag{12}$$

$$\Omega_{h} = \frac{S_{h} + J_{mr} \check{S}_{m} \cos \Gamma_{v}}{J_{h}(\Gamma_{v})}$$
(13)

$$\frac{du_{hh}}{dt} = \frac{1}{T_{tr}} (-u_{hh} + K_{tr} u_h)$$
(14)

$$\check{S}_t = P_h(u_{hh}) \tag{15}$$

Assume the tail rotor is an independent system, then (11) to (15) can be written as:

$$\frac{dS_h}{dt} = l_t F_h(\check{S}_t) \cos \Gamma_v - \Omega_h k_h \tag{16}$$

$$\frac{d\Gamma_h}{dt} = \Omega_h \tag{17}$$

$$\Omega_h = \frac{S_h}{h} \tag{18}$$

$$\frac{du_{hh}}{dt} = \frac{1}{T_{tr}} (-u_{hh} + K_{tr} u_h)$$
(19)

$$\check{\mathsf{S}}_{t} = P_{h}(u_{hh}) \tag{20}$$

Block diagram of tail rotor is shown in Fig .5.



Fig. 5. Block diagram of tail rotor.

III. DESIGN OF NEURO-SLIDING MODE CONTROL

In the proposed structure, the equivalent control term, in sliding mode is computed by an NN. The output of the NN is summed with the corrective term to form the control signal. The corrective control is accepted as a measure of the error to update the weights of the NN [8]. The aim of the learning process of the NN is to minimize the corrective control .This is because in sliding mode the equivalent control is enough to

keep the system on the sliding surface and the corrective term is necessary to compensate the deviations from the surface [5].The overall system with the proposed controller is given in Fig.6.

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Fig. 6. The structure of NSMC.

A. Computation of the equivalent control

The NN is chosen to be a three –layer feed –forward NN which has one input layer, one output layer and the hidden layer. The structure of inputs and the output of the network are established by the equivalent control equation [8]. The structure of NN used to generate U_{eq} is presented in Fig.6.

From the Fig.6, it found that the equivalent control is computed by using the iterative gradient algorithm to minimize the mean square error between the desired and actual states. The symbols used in Fig.7 are defined as follows. Let Z_i be the input to the i-th node in the input layer, Y_{net_i} be the input to jth node in hidden layer, and the output of hidden layer be Y_{out_i} .Similarly the input and output of the output layer are designated as Unet and Uout, respectively .Furthermore, $W_{z_{i,j}}$ means the weight between the input layer and the hidden layer and output layer. In this paper we use two NN, one from the vertical part and other from the horizontal part. The NN is chosen to be a three input neurons and six hidden neurons for each part vertical and horizontal.



Fig.7. The structure of NN to estimate the equivalent control

The values can be computed as::

$$Ynet_j = \sum_{i=1}^3 W z_{i,i} \cdot Z_i \tag{21}$$

$$Yout_j = g(Ynet_j)$$
(22)

$$Unet = \sum_{j=1}^{6} Wy_j \cdot Yout_j$$
(23)

$$Uout = g(Unet)$$
 (24)

$$u_{eq-Neuro} = \hat{U}_{eq}(t) = K_{eq} \cdot Uout$$
⁽²⁵⁾

$$g(x) = \frac{2}{1 + e^{-x}} - 1 \tag{26}$$

The activation function g(x) is selected as a sigmoid transfer function . K_{eq} is a constant that represents the maximum available value of the equivalent control. Thus $\widehat{U}_{eq}(t)$ is the estimated value of the equivalent control . In order to prevent the equivalent control from exceeding the maximum bound of the actuator or reaching an unreasonably large value , the output of the neural network is keep in [1,-1]. In a general NN ,the backpropagation uses the gradient descent method to establish the multilayer feed forwardnetwork. The training processes use iterative gradient algorithms to minimize the mean square error between the actual output and the desired output , i.e., to minimize the cost function selected as the difference between the desired and the estimated equivalent controls. Hence a simple cost function is defined as follows

$$E = \frac{1}{2} \cdot \left(U_{eq} - \widehat{U}_{eq} \right)^2 \tag{27}$$

The objective is to minimize the error function E by taking the error gradient with respect to the weights. The weights are updated by using

$$(Wy_j(t) = Wy_j(t-1) - \alpha \cdot \frac{\partial E}{\partial Wy_j}$$
 (28)

$$Wz_{ij}(t) = Wz_{ij}(t-1) - \alpha \cdot \frac{\partial E}{\partial Wz_{ij}}$$
(29)

Where α is a constant that denotes the learning rate parameter of the backpropagational gorithm. Moreover the two terms Wy₁ and $\partial W_{z_{11}}$ can be derived as follows

$$\frac{\partial E}{\partial W y_j} = -\left[\left(U_{eq} - \hat{U}_{eq} \right) \cdot K_{eq} \cdot \frac{1}{2} \cdot (1 - g(Unet)^2) \right]$$

$$\cdot Yout_j$$
(30)







$$\frac{\partial E}{\partial W z_{ij}} = -\frac{1}{4} \cdot \left| \left(U_{eq} - \widehat{U}_{eq} \right) \cdot K_{eq} \cdot (1 - g(Unet)^2) \cdot W y_j \right| \cdot \left(1 - g\left(Ynet_j \right)^2 \right) \cdot Z_i$$
(31)

Notice that the actual equivalent control U_{eq} in (30) and (31) is unknown .Hence (28) and (29) cannot be calculated .In order to overcome this problem .the value of corrective control U_c is utilized to replace $U_{vq} - \hat{U}_{eq}$. The reason is that the characteristics of $U_{eq} - \hat{U}_{eq}$ and corrective control are similar. [9]

B. Computation of the corrective control

The equivalent control is to keep the system states at the sliding surface S=0 forall $t \leq 0$. Hence, if the states is out-side the sliding surface, to drive the state to the sliding surface, we choose the control law such

$$SS < - |S| \tag{32}$$

Where is a positive constant, and (2-9) is called reaching condition. The control objective is to guarantee that the state trajectory can converge to the sliding surface. So, we define the corrective control, which are shown as follows.

$$U_c = Ksgn(S) \tag{33}$$

Where K is a positive constant. The sign function is a discontinuous function as follows:

$$sgn(S) = \begin{cases} 1, S > 0\\ 0, S = 0\\ -1, S < 0 \end{cases}$$
(34)

Hence, the whole control input (u) is a combination of U_{eq} and U_c

$$u = u_{ea} + u_c \tag{35}$$

Notice that the (33) exhibits high frequency oscillations, which is defined as chattering. Chattering is undesired because it may excite the high frequency response of the system. Basically, the common methods to eliminate the chattering are usually adopting the following. 1) Using a saturation function .2) Inserting a boundary layer [3], so an equivalent control replaces the corrective one when the system is inside the boundary layer. This method can give a chattering-free system, but a finite steady-state error would exist. Since the most popular technique is the saturation function, this method can abate the problem of high-frequency oscillation of the control input. Hence, to eliminate the chattering, most of approaches [3]–[6], use the saturation or the signoid function to replace the sign function. In this paper, for the chattering elimination, the corrective control will be chosen as:

$$U_c = Kg(S) \tag{36}$$

IV. SIMULATION RESULTS

The input of the neural network (designed as Z) consisted of the actual state and other parameters as: $z_v = [\alpha_v s_v u_{vv}]$ and $z_h = [\alpha_h s_h u_{hh}]$ and all the network weights were initialized to small random values between [-0,05, 0,05].

The proposed neural sliding mode control scheme presented in this paper was tested on helicopter setup, which is called a twin rotor MIMO system. The control object is to make the beam rotate quickly and accurately in accordance with time-varying reference signals of the pitch angle a_v , and the azimuth angle a_h .

The results of using the proposed control strategy are shown in Fig .8. From the results, we can find that chattering phenomenon of the controlled system was suppressed in the proposed controller. Moreover, in the NSMC we did not need to compute the dynamical equation of the system and the equivalent control estimated by the NN.









Fig.8 Simulation results of NSMC applied to the TRMS .

V. CONCLUSION

In this paper an NSMC was proposed for a TRMS system and simulation results were presented. The NN was used to compute the equivalent control term .The structure of the NN that estimates the equivalent control was a standard three layer feed forward NN with the backpropagation adaptation algorithm. The corrective control was accepted as a measure of error to update the weights of NN.

The proposed method has the following advantages:

1) There is no need to know the dynamical equation of a system to compute the equivalent control.

2) Chattering and the excessive activity of the control signal are eliminated without a degradation of the traking perfermance .

3) The learning process is online .Learning and calculation of the equivalent control signal are carried out simultaneously.

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