EPJ Web of Conferences **343**, 05015 (2025) https://doi.org/10.1051/epjconf/202534305015
AIMACE-2025

Neural Network Based Flight Attitude Control Using Robust Sliding Mode

Prabhjeet Singh[1,*], *Salahudden* Salahudden[1], *Rakesh* Kumar[2], and *Tushar* Siag[3]

[1]Assistant Professors, Department of Aerospace Engineering, Punjab Engineering College (Deemed to be University), Chandigarh – 160012, India
[2]Professor, Department of Aerospace Engineering, Punjab Engineering College (Deemed to be University), Chandigarh – 160012, India
[3]Doctoral Candidate, Department of Mechanical and Aerospace Engineering, FAMU FSU College of Engineering, Florida, USA

Abstract. In this article, an adaptive sliding mode control (SMC) strategy is designed for the attitude control of aircraft under the influence of dynamic disturbances. A radial basis function neural network (RBFNN) is integrated with the SMC framework, effectively handling the nonlinear aerodynamic forces and moments. This network adapts through the variation in weights and provides a real-time function approximation in order to improve the robustness of the controller against uncertainites. A sigmoid function is incorporated for smoother control input to reduce the chattering effect which is found commonly in SMC. The control strategy has been formulated using only partial information from the aerodynamic model based on available physical parameters of the plant. Its effectiveness is verified through the use of a quadratic Lyapunov function which helps confirm that closed loop system remains stable and the states stay within bounded limits. The simulations show that the control method works well, as it follows the desired attitude commands closely and keeps performing reliably even when different disturbances are introduced.

1 Introduction

Controlling the attitude of an aircraft is essential for both its stability and its ability to maneuver, especially since it is usually the first thing adjusted by a pilot or autopilot when something unexpected occurs. Unfortunately, achieving accurate attitude control is not straightforward because of the nonlinear behavior of aerodynamic forces which becomes even more difficult in rapidly changing conditions. Because of these challenges, attitude control has become a major focus of research in aerospace control systems. In recent years progress in this area has extended to a wide range of systems such as satellites, unmanned aerial vehicles, and conventional aircraft, highlighting its importance in both military and civilian operations [1–3].

SMC has drawn considerable interest over the years, mainly because of its strong ability to deal with system uncertainties and external disturbances effectively [4, 5]. That being said, one of the known drawbacks or disadvantage of this approach is the occurrence of rapid and high frequency oscillations which is often referred to as chattering. To reduce this effect,

*e-mail: prabhiitk@gmail.com

many studies have introduced smooth transition functions such as sigmoid function into the control law which helps produce less abrupt control signals [6]. At the same time RBFNN have been proven useful for estimating nonlinear behaviors which makes them a valuable addition to control design [7, 8]. Their universal approximation capability has made them highly suitable for applications where accurate aerodynamic model information is actually unavailable. The combination of RBFNNs with adaptive control enables good estimation of dynamic parameters which ultimately enhance robustness of the control system. Infact, studies have demonstrated the effectiveness of combining RBFNNs with SMC for different aerospace applications which includes trajectory tracking and disturbance rejection [9].

Based on this foundation, the current work introduces an adaptive sliding mode control framework for the attitude control of an F-16 aircraft. The wind tunnel data for the F-16 is readily available in the public domain at moderate angles of attack. This data actually facilitates the validation and comparison of our simulation results, bridging the gap between computational models and real-world performance. Unlike traditional approaches, controller proposed in this paper leverages an RBFNN for real-time approximation of unknown aerodynamic forces and moments which reduces the dependency on detailed aerodynamic models. A sigmoid function is incorporated into the sliding mode framework to alleviate disturbance and chattering effects which ensures smoother control inputs. The controller design is validated using a quadratic Lyapunov function and hence guarantees closed-loop stability and uniformly bounded states. Thereby, this paper makes an attempt in addressing a critical gap in the field of flight control systems which is the need for robust and adaptive controllers that can handle nonlinearities and disturbances in real-time without relying completely on detailed aerodynamic models. Traditional SMC methods are robust but susceptible to chattering and a lack of adaptability to dynamic conditions. The integration of RBFNN within the SMC framework bridges this gap, providing a scalable solution that enhances both robustness and smoothness of control inputs.

The key contributions of this paper involve the development of an adaptive sliding mode control strategy integrated with an RBFNN to handle nonlinear aerodynamic forces and moments in attitude control. Further, reduction of chattering and disturbance mitigation through the incorporation of a sigmoid function is achieved, resulting in smoother control performance while maintaining robustness. The remainder of the paper is organized as follows. The next section presents the problem definition along with the controller design. Thereafter, simulation results are provided to evaluate the controller's performance. Finally, the last section concludes the paper and highlights potential directions for future research.

2 Problem Definition with Controller Design

For the aircraft dynamics, the full mathematical model is considered in this article is derived from [10]. Only the rotational kinematic equations are repeated here to make this paper as self sufficient.

$$\begin{aligned} \dot{\phi} &= p + q\sin\phi\tan\theta + r\cos\phi\tan\theta \\ \dot{\theta} &= q\cos\phi - r\sin\phi \\ \dot{\psi} &= (q\sin\phi + r\cos\phi)\sec\theta \end{aligned} \tag{1}$$

The symbols used above have established meanings in flight mechanics research community. Since the motive is to regulate attitude angles, the sideslip is assumed to be zero. Eq. 1 is differentiated to yield the equation in the following format.

$$\ddot{x}(t) = f(x,t) + g(x,t)\,u(t) + d(t) \tag{2}$$

Here, f and g are nonlinear functions, x represents the system states, u is the control input, and d denotes the external bounded disturbance, satisfying $|d| \leq \Delta$. Equation 2 can be conveniently expressed in state-space form as follows:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= f + g\,u + d \end{aligned} \tag{3}$$

Here, x_1 and x_2 represents the Euler angles and angular rates, respectively. Now, we can begin designing the control law which will steer x_1 to its constant desired value (x_d). We design the sliding surface as $S = Ke + \dot{e}$, where $K > 0$ and $e = x - x_d$. The derivative of sliding surface yields $\dot{S} = K\,x_2 + f + g\,u + d$. We design Lyapunov function candidate L to be quadratic as follows.

$$\begin{aligned} L &= \frac{1}{2}S^2 + \frac{1}{2\Gamma}\widetilde{W}^T\widetilde{W} \\ \dot{L} &= S\,(Kx_2 + f + g\,u + d) + \frac{1}{\Gamma}\widetilde{W}^T\dot{\widehat{W}} \end{aligned} \tag{4}$$

Here, $\Gamma_1 > 0$ denotes the adaptation gain, and $\widetilde{W}^T = \widehat{W}^T - W^{*T}$ represents the weight estimation error, where W^{*T} and $\widehat{W}^T$ are the ideal and estimated weight vectors, respectively. These vectors are updated online using adaptation laws based on Lyapunov theory. The error associated with the unknown nonlinear function f is expressed as follows:

$$\begin{aligned} \widetilde{f} &= f - \widehat{f} \\ &= W^{*T}h\,(x) + \nu - \widehat{W}^T h(x) \\ &= -\widetilde{W}^T h(x) + \nu \end{aligned}$$

Here, ν is the small neural approximation error and h represents Gaussian member given as

$$h_j = exp\left(-\frac{\|x - \mu_j\|^2}{2b_j^2}\right)$$

Here, μ and b represent the centers and the width of the Gaussian function, respectively [11]. To ensure that $\dot{L}$ satisfies Lyapunov criteria, the control input is formulated as follows:

$$u = \frac{1}{g}\left\{-Kx_2 - \widehat{f} - \frac{\rho\,S}{|S| + \epsilon}\right\} \tag{5}$$

where $\widehat{f}$ is the estimated nonlinear function and a sigmoid function is used to tackle the disturbance term. Here, $\rho > 0$ and ϵ is a small positive scalar [6]. Finally, substituting Eq. 5 in Eq. 4, we get

$$\begin{aligned} \dot{L} &= \nu S - \frac{\rho}{|S| + \epsilon}S^2 + S\,d - S\,\widetilde{W}^T h(x) + \frac{1}{\Gamma}\widetilde{W}^T\dot{\widehat{W}} \\ &= \nu S - \frac{\rho}{|S| + \epsilon}S^2 + S\,d + \widetilde{W}^T\left[\frac{\dot{\widehat{W}}}{\Gamma} - S\,h(x)\right] \end{aligned}$$

We design $\dot{\widehat{W}}$ such that the last term vanishes, i.e., $\dot{\widehat{W}} = \Gamma S\,h(x)$ and finally the derivative of Lyapunov candidate yields

$$\dot{L} = \nu S - \frac{\rho}{|S| + \epsilon}S^2 + S\,d$$

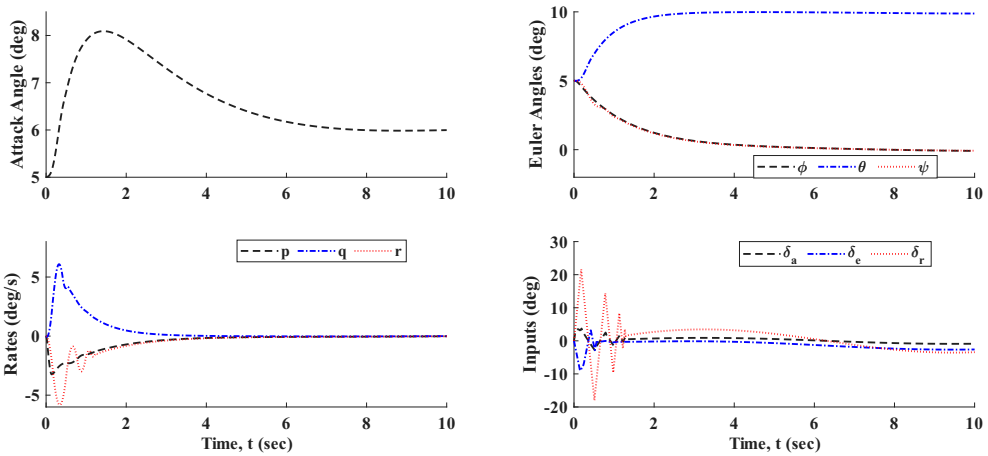

Figure 1. Time history of the aircraft states, attack angle and control inputs.

Here, we choose ρ such that $\rho \geq \Delta$ and with proper selection of the centers and width, the neural approximation error is in close proximity to zero. Hence, we can infer that $\dot{L}$ yields to be negative semi-definite function and the regulation task is achieved as $t \to \infty$. Next, we demonstrate the effectiveness of proposed control law.

3 Simulation Results

The computational analysis will now evaluate the robustness of the neural network-based flight attitude control system implemented using a sliding mode controller, as developed earlier in this study. The model used in this paper is similar to that used in [12–14], except where explicitly indicated. The initial conditions for the system states considered are $\alpha = 5°$, $p = q = r = 0$, $\phi = \theta = \psi = 5°$. Here, disturbances are intentionally included in the aerodynamic model to test the effectiveness of the control law. The amplitude and frequency of the disturbance are taken as 0.1 and 0.5 rad/sec, respectively. The disturbance is acting throughout the course of the simulation run time. The simulation begins with the aircraft flying level at an altitude of 25000 ft and a total aerodynamic velocity of 150 m/s. According to [15], the aircraft's maximum thrust, T_{max}, is approximately 10000 lb under standard atmospheric conditions. In an attempt to bridge the gap between the computer simulations and the realistic model, the control logic employed in the present paper inculcates the position and the rate limit of the control surface deflections.

The simulation environment was meticulously designed to replicate realistic flight conditions for the F-16 aircraft. The model was implemented using MATLAB/Simulink, a powerful tool for control system design and analysis. The simulations were conducted on a high-performance computing with Intel i9 processor and 32 GB of RAM, ensuring accurate and efficient computation. Runge Kutta fourth order method was employed with a time step of 0.01 seconds for numerical simulation. These resources and methodologies ensured a robust and reliable evaluation of the proposed control law.

To regulate Euler angles, the gains used for the simulation run are as follows: $K_1 = 0.75$, $K_2 = 1.5$, $K_3 = 0.75$, $\epsilon = 0.01$, $\rho_1 = \rho_2 = \rho_3 = 2$. The gains were selected in such a way that it ensures rapid convergence of the sliding surfaces while maintaining smooth control inputs. The disturbance rejection parameter was set based on the upper bound of

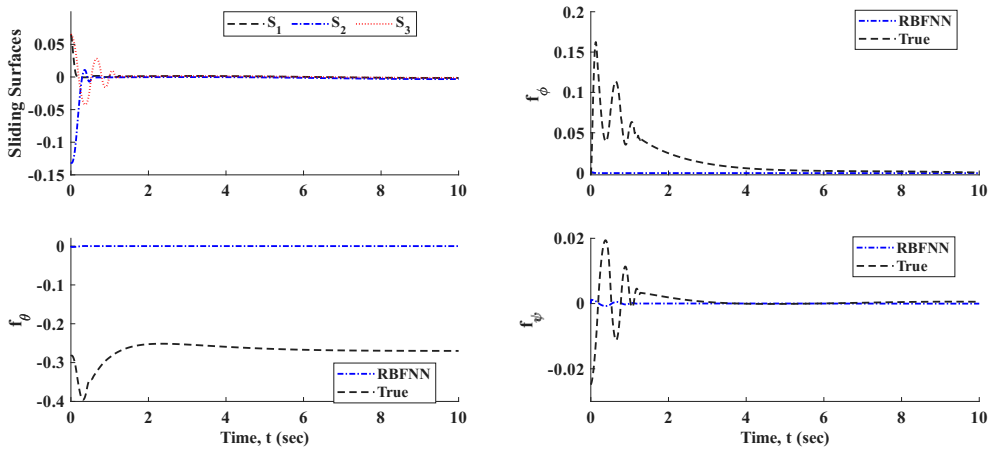

Figure 2. Time history of the sliding surfaces and function approximations for the Euler angles.

anticipated disturbances. A small positive scalar was chosen to prevent singularity in the control law formulation. In terms of function approximation, the model comprises two input layers, five hidden nodes, and one output dedicated to attitude dynamics. The input layer is defined by the orientation angles and their corresponding angular rates. The centers are uniformly distributed across the intervals $[-1, 1]\times[-1, 1]$, with a width of unity. Initialization of the adaptive weights is considered zero. The desired Euler angles are as follows: $\phi_d = \psi_d = 0°, \theta_d = 10°$ and the aerodynamic velocity during the simulation run is considered to be constant here.

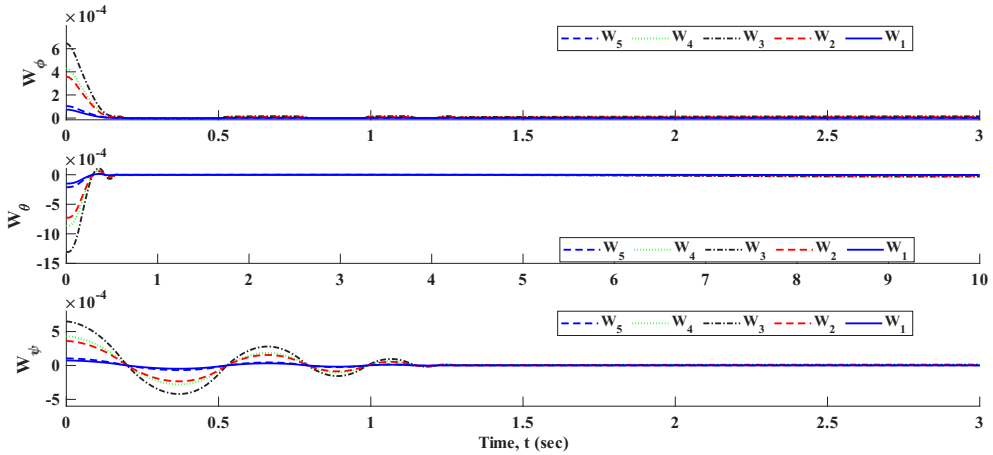

Figure 3. Time history of the adaptive weights for the Euler angles.

The results of the proposed controller for a highly non-linear system can be seen in Fig. 1, where the Euler angles are regulated to their respective desired values. In the process, the attack angle variation is also regulated to $\approx 6°$, i.e., settle at its respective equilibrium point. It can also be observed that the angular rates are driven to zero in about 5 *sec*. There is a noticeable yet acceptable variation in the control inputs due to the continuous disturbances

experienced during the simulation run. The sigmoid function present in the control law not only rejects the external disturbances but also ensures smooth transition in the control inputs, avoiding the phenomenon of chattering. Figure 2 represents the time history of sliding surfaces along with the estimated and true RBFNN functions. The plot indicates that the states converge to $S = 0$ and stay there for remainder of duration, which further validates suitability of the surface chosen. Moreover, it is observed that, apart from $\hat{f}_\theta$, only $\hat{f}_\phi$ and $\hat{f}_\psi$ converge to zero. It is imperative to highlight that $\hat{f}$ need not to converge to the real f, as tracking could be achieved through many values of nonlinear function [11]. Finally, Fig. 3 illustrates the adaptation of neural network weights over time under dynamic conditions, highlighting the network's learning and adaptation capabilities. These adaptive weights are continuously updated in real time and eventually approach near-zero values once the desired state is attained.

The simulation results clearly demonstrate the superiority of the proposed neural network-based sliding mode control approach. Unlike conventional SMC, which often struggles with high-frequency oscillations and limited adaptability to dynamic uncertainties, the integration of RBFNN allows real-time approximation of unknown dynamics. These improvements make the control system much robust overall. In practical cases this approach deals well with disturbances and changes in system parameters which is actually very crucial for real world aerospace applications. For example, sigmoid function aids in smoothing out the actuator signals which is critical for aerodynamics control surfaces. Also, the adaptive tuning of weights helps the controller respond adaptively to changes in system behaviour. These benefits make it a good candidate for use in next generation flight control setups where uncertainty cannot be entirely avoided.

4 Conclusions

This work highlights the significance of combining neural networks with sliding mode for achieving robust attitude control. The proposed controller in this paper maintained balance between stability and robustness while overcoming the nonlinear aerodynamic effects and disturbances. The use of neural networks in adaptive tuning of weights actually enables the system to respond effectively to unknown dynamics in the plant. At the same time, a sigmoid function helps reduce the typical chattering behaviour which is seen in SMC and eventually leads to smoother actuator signals. The simulation results support these claims showing good tracking of attitude reference signals.

This study can be further explored in several future research directions such as expanding the control approach to larger flight envelopes. Another key direction would be the hardware in the loop testing which can include effects of sensor noise and actuator delays. Further, this method can be combined with model predictive control or reinforcement learning which may further improve its efficacy.

5 Acknowledgment

The authors gratefully acknowledge Vaishali for her valuable discussions, which contributed significantly to enhancing the clarity and presentation of this paper.

References

[1] Hu, Q., and Tan, X., *Dynamic near-optimal control allocation for spacecraft attitude control using a hybrid configuration of actuators*, IEEE Transactions on Aerospace and Electronic Systems, Vol. 56, No. 2, 2019, pp. 1430–1443.

[2] Tayebi, A., and McGilvray, S., *Attitude stabilization of a VTOL quadrotor aircraft*, IEEE Transactions on control systems technology, Vol. 14, No. 3, 2006, pp. 562–571

[3] Zhang, J., Yang, L., and Shen, G., *Modeling and attitude control of aircraft with center of gravity variations*, 2009 IEEE Aerospace conference, IEEE, 2009, pp. 1–11

[4] Jafarov, E., and Tasaltin, R., *Robust sliding-mode control for the uncertain MIMO aircraft model F-18*, IEEE Transactions on Aerospace and Electronic Systems, Vol. 36, No. 4, 2000, pp. 1127–1141

[5] Singh, P., Giri, D. K., Ghosh, A. K., et al., *Attitude Control of Hansa-3 Aircraft with Perturbation Using Sliding-Mode Controller*, IEEE Aerospace Conference (AERO), IEEE, 2022, pp. 1–9

[6] Shtessel Y., Edwards C., Fridman L., Levant A., *Sliding mode control and observation*. New York: Springer New York, 2014.

[7] Hornik, K., *Approximation capabilities of multilayer feedforward networks*, Neural networks, Vol. 4, No. 2, 1991, pp. 251–257

[8] Cybenko, G., *Approximation by superpositions of a sigmoidal function*, Mathematics of control, signals and systems, Vol. 2, No. 4, 1989, pp. 303–314

[9] Xiao H., Zhen Z., Xue Y., *Fault-tolerant attitude tracking control for carrier-based aircraft using RBFNN-based adaptive second-order sliding mode control*. Aerospace Science and Technology. 2023 Aug 1; 139:108408

[10] Fan, Y., Lutze, F., and Cliff, E., *Time-optimal lateral maneuvers of an aircraft*," Journal of Guidance, Control, and Dynamics, Vol. 18, No. 5, 1995, pp. 1106–1112

[11] J. Liu, *Radial Basis Function (RBF) Neural Network Control for Mechanical Systems: Design, Analysis and Matlab Simulation*, Springer Science & Business Media, 2013.

[12] Singh, P., Giri, D. K., and Ghosh, A. K., *Robust sliding mode augmenting integral backstepping for lateral-directional control of a highly maneuverable aircraft*, Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering, Vol. 237(10), p. 2428-2441, 2023

[13] Singh P., Giri, D. K., Ghosh, A. K., *Neuro-Backstepping Sliding Mode Flight Control using Asymmetric Barrier Lyapunov Function*. In AIAA AVIATION 2023 Forum 2023 (p. 3800).

[14] Singh P., Giri, D. K., Ghosh, A. K., *Arbitrary Prescribed-Time Disturbance Observer-Based Neural Backstepping using Time-Varying Asymmetric BLF*. In AIAA AVIATION 2023 Forum 2023 (p. 3799).

[15] Nguyen, L. T., *Simulator study of stall/post-stall characteristics of a fighter airplane with relaxed longitudinal static stability*, Vol. 12854, National Aeronautics and Space Administration, 1979.