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Neuronal Slidding Mode Output Control Application in a Attitude for Quadrotor

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***Abstract*—The primary goal of this research report is to investigate the challenging topic of flight dynamics control-regulation over a quadrotor UAV's orientation (attitude) in the presence of wind disturbances and unmodeled dynamics. To do this, we first create a viable output feedback controller-regulator that incorporates Filters High Gain Observers (FHGO) of ultimate generation, feedback and Radial Basis Function Neural Network (RBF) compensation of estimated disturbances. Furthermore, the usage of reliable sliding mode controllers. Then, despite wind dynamics, noise in sensor outputs, velocity estimates, and common modeling mistakes, a quadrotor UAV is maintained at a given orientation utilizing such a controller. Finally, the effectiveness of the suggested controller is investigated in a simulation framework using a realistic physical model of a quadrotor UAV.**

***Index Terms*—Quadrotor, Observers, Nueronal Networks, Sliddig Mode**

I. Introduction

Unmanned Aerial Vehicles (UAVs, often known as drones) have seen tremendous expansion in the previous decade. This is due to UAVs' capacity to accomplish a wide range of tasks at minimal prices while also carefully managing human resources. Drones are being utilized for various outdoor operations, including surveillance, agricultural services, mapping and photography, war damage assessment, and border interdiction prevention, to name a few [1].

It is necessary to ensure an appropriate position and attitude UAV control to complete the applications mentioned above. This type of control must be able to withstand wind gusts. Drone photography for environmental research of rivers and watersheds is one of the most recent drone uses, allowing for estimating key morphometric characteristics of these ecological systems such as volume, surface, length, and depth, among others [2].

Some research has developed control algorithms for drones to prevent wind impacts. The authors use an extended state observer to predict aerodynamic disturbances for a UAV coaxial-rotor in [3]. Innovative approaches in mission management of current and future generation air vehicles have resulted from technological advances in the field of external disturbance rejection, such as wind . This sort of vehicle's extremely nonlinear and coupled dynamics are ideal for researching both linear and nonlinear control methods for disturbance rejection tasks. For a UAV's performance, wind gust disruptions, model errors, and nonlinear behaviour are unavoidable. In practice, dynamic uncertainties like unmodeled external forces and moments make it difficult for an open-loop control strategy to follow the planned trajectory. Therefore many works have explored the robust control of autonomous vehicles such as quad rotors from adaptive techniques, and these techniques have shown remarkable performance [1], [4]–[6]. Also, modern robust techniques such as Backstepping have been used in the literature in recent years; these techniques show outstanding robustness in maintaining complicated tracking trajectories [7]–[10]. This technique has been combined with a powerful tool called sliding mode to further improve the robust control problem. Typically these techniques have a significant advantage in the robustness of nonlinear systems in the presence of disturbances [11]–[14]. Still, there is a lack of complete knowledge of the functions such as wind. These disturbances can decrease the effectiveness, even causing real issues in its implementation, such as Chateting [15], [16]. A possible improvement to the performance of sliding mode control is the use of artificial intelligence technologies, such as neural networks. This tool has recently seen a boom in its application in control and estimation tasks in robotic systems [17]. In particular, neural networks have been used in drones and these have shown great performance in tracking control tasks. Their application is aimed at estimating unknown functions and even variables, which significantly helps in the excellent performance of robust controllers [18]–[20]. The combination of neuronal networks with control by Sliddig modes applied to the rejection of disturbances in quadrotors is a very recent topic to study. Currently, there are few works, such as, which has shown a significant advance in achieving conditions and performances of good quality in the robust control of UAV's [21]. On the other hand, Filtered High Gain Observers (FHGO) are cutting-edge algorithms that are being studied in recent papers [22]–[24]. They have already been compared to other types of estimators, and this type of observer performs better in the suppression of uncertainty, particularly in the avoidance of noise in the outputs.

In this conference paper, we show an exploratory study on the use of neural networks to estimate unknown functions in nonlinear systems (quadrotors) and their use in the calculate of robust control laws of sliding mode. In addition, the use of Filtered High-Gain Observers (FHGO, see paper [22]) to estimate the speed in the presence of noise at the output (angular position) is explored. The FHGO is an improvement to the classical High Gain Observers (HGO) since it is known that these present problems in noise at the outputs. To our knowledge, few works mix the techniques mentioned herein quadrotor control problems.

In the first stage, a small contribution is made to the mathematical model of the quadrotor. In the second section, the basic concepts to be used are emphasized. In the third section, the main results to be used are presented. The fourth section deals with the numerical study that aims to demonstrate the use of the techniques. And finally, the conclusions of the work are shown.

II. A Model a quadrotor

Consider the quad-rotor is modeled as a rigid body, and its whole dynamics are described as follows in terms of rotational and transnational dynamics [25]:

$$\Sigma_1 : \left\{ \; m\ddot{\xi} \;\; = \;\; -ge_{z_{\mathcal{I}}} + uR \right. \tag{1a}$$

$$\Sigma_2 : \left\{ \; \mathbb{J}\ddot{x} \;\; = \;\; -C(x,\dot{x})\dot{x} + u_T(t) \right. \tag{1b}$$

where subsystem determines the quadrotor's position and altitude dynamics Σ_1 and Σ_2 respectively; ξ and $\dot{\xi}$ are the aircraft's location and velocity in relation to the inertial frame. Euler angles; $x = (\phi, \theta, \psi)^{\intercal}$. The term m represents quadrotor mass, $e_{z\tau}$ position error and u is the control used in stage.The aforementioned systems are not disjoint; it is obvious that the attitude change dynamics modify the position dynamics; in this study, we focus primarily on the control of attitude change dynamics (1b).

The above model is the global form of the dynamics of a quadrotor. Given that the first step is to stabilize the orientation or attitude of a drone, in this paper, we will focus on the Σ_2 model. The $u_T(t) \in \mathbb{R}^3$ are the force and torque vectors applied to the MAV's center of mass, respectively. $C(x, \dot{x})$ is the Coriolis matrix which contains the gyroscopic and centrifugal terms associated with the Euler angles dependence of $\mathbb{J}$ As known from previous research and it is defined as Inertial Matrix. Coriolis terms are extremely complex to know in real time, so this term is often considered as an unknown but bounded term [3]. It is known in the literature that to control a drone in its longitudinal phase [26], it is necessary first to be able to control the orientation, and on this to be able to design a longitudinal controller. This work will focus on developing a robust controller in orientation to reject the disturbances generated by unknown dynamics or wind over the Euler angles of the following model. The wind gusts are a main disturbances present in the outdoor tasks. Therefore, the following perturbed attitude model is proposed for the system Σ_2(1b)

$$\mathbb{J}\ddot{x} = -C(x,\dot{x})\ddot{x} + u_T(t) + w(t) \tag{2}$$

where $w(t)$ is the disturbance vector due to uncertain functions and wind perturbations.It has been shown in the literature that it is necessary to make assumptions, in this work we rely on the following [3], [24], [26] Therefore it is proposed the following assumptions:

Assumption 1 Matrix $\mathbb{J}$ is known and approximated as a non-negative diagonal matrix.

Assumption 2 Coriolis matrix $C(x, \dot{x})$ is a Lipschitz state function and it satisfies $\|C(x', \dot{x}) - C(x, \dot{x})\| \leq l_c \|x' - x\|$ $\forall\, x' \neq x$ and $l_c > 0$.

Assumption 3 The disturbance $w(t)$ is a bounded vector disturbance that satisfies $\|w(t)\| \leq w_{\max}$, where $w_{\max}$ is a nonzero positive constant.

Assumption 4 The effect of wind on the vehicle produces a torque on the quadrotor such that this effect is unknown but it is bounded to a nonlinear function. Such that this function is differential continuously and bounded $d(\dot{x}, x, t) = w(t) - C(x, \dot{x})\dot{x}$.

Note 1: It is important to mention that since there is a nonlinear $d(\dot{x}, x, t) = d(t)$, the attitude angles are decoupled. Therefore it is possible to reject to reject the wind effect at each angle independently, as a [27].

$$d(t) = \begin{pmatrix} d_{1,\phi}(t) \\ d_{2,\theta}(t) \\ d_{3,\psi}(t) \end{pmatrix} \quad \forall \in \mathbb{R}^3$$

Also, position $x(t)$ are known based on analog or digital sensor technology but we propose to estimate the rotation rate $\dot{x}(t)$ thank to a high gain observer, for this task we proposed to used a high gain observer. The disturbance function $d_x(t)$ is infeasible to measure in real time, but it is reject via a robust control. In addition, as mentioned above, this work relies on the assumption that the dynamics of the three axes can be decoupled and rejected independently, which had already been proposed in other works [2], and another one by [3].Therefore, based on the above assumptions, the general attitude math model (3) can be rewritten as follows:

$$\begin{aligned} \ddot{x} &= \mathbb{J}^{-1}(u_T(t) + d(t)) \\ y &= Cx \end{aligned} \tag{3}$$

For element $j = (\phi, \theta, \psi)$, with the torque in 3 angles as:

$$u_T(t) = \begin{pmatrix} u_{\phi(t)} \\ u_{\theta(t)} \\ u_{\psi(t))} \end{pmatrix} \quad \forall \in \mathbb{R}^3$$

and

$$\mathbb{J}^{-1} = \begin{pmatrix} \alpha_\phi^{-1} & 0 & 0 \\ 0 & \alpha_\theta^{-1} & 0 \\ 0 & 0 & \alpha_\psi^{-1} \end{pmatrix} \quad \forall \in \mathbb{R}^{3x3}$$

Where $\mathbb{J}$ is a non singular matrix and is also known in decoupled systems. Also $x_1 = x$ and $x_2 = \dot{x}_1$ are defined. This equation (3) can be written as:

$$\ddot{x}_j = \alpha_j^{-1} u_j + \alpha_j^{-1} d_j(t) \tag{4}$$

This model can be seen as a sum of a linear and a nonlinear part. This characteristic allows to use control techniques such as active perturbations rejection together with sliding mode control. This situation will be discussed in the next section.

Thus, by setting $x_j = (x_{1,j}, x_{2,j})^T \in \mathbb{R}^{2x1}$, $y_j = x_{1,i}$, the model (4) can be expressed in the form of a strict triangular system (i.e. the canonical observability form) as following:

$$\begin{aligned} \dot{x}_j &= Ax_j + G(u_j(t) + d_j) \\ y_j &= Cx_j \end{aligned} \tag{5}$$

where:

$$\begin{aligned} A &= \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \in \mathbb{R}^{2x2} \\ G &= \begin{bmatrix} 0 \\ \alpha_i^{-1} \end{bmatrix} \in \mathbb{R}^{2x1} \\ C &= \begin{bmatrix} 1 & 0 \end{bmatrix} \in \mathbb{R}^{1x2} \end{aligned}$$

It should be noted that the aforementioned model is a nonlinear model with linear and nonlinear components; the uncertainties d_j will be evaluated and estimated using the approaches described in this article.

III. Output Feedback Robust Control Designed

As mentioned above, this paper explores the novel use of the FHGO neural network estimator in conjunction with the computation of robust control law, a sliding mode SMC, illustrated to Figure 1. The first step consists of state estimation and estimation of unknown functions via the neural network.

Assumption 5 The reference function is represented by a continuously differentiable function.

A. A Filter High gain Observer (FHGO)

State estimation is essential when sensors are of poor quality, expensive, or difficult to access. In the specific case of quadrotors, it is known that many of the angular velocity sensors perform poorly concerning the quality of the angular position sensors, which is the reason for the use of observer-type state estimators. The FHGO observer is a very recent and novel theoretical and practical contribution. It is an improvement of the classical high gain observer since it improves the previous problems of Gaussian noise in the outputs, which is generated by analog or digital sensors. In [22], a robust observer to uncertainties and noise in the output has been proposed. Thus, based on this, the following FHGO observer is proposed for the model (5):

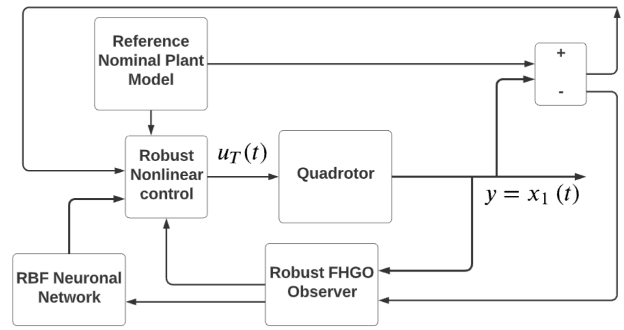

Fig. 1. Schematic diagram of the robust control approach.

$$\begin{aligned} \dot{\hat{x}}_j &= F(u_j, \hat{x}_j)\hat{x}_j + \varphi(u_j, \hat{x}_j) - hK(t)z(t) \\ \dot{z}_j &= \delta h\{-\phi_j(t) + hA^T z(t)\} + C_{qn1}^T (C\hat{x}_j - y_j) \\ z(0) &= 0 \end{aligned} \tag{6}$$

where $\hat{x}_j = \begin{bmatrix} \hat{x}_j^{(1)} \\ \vdots \\ \hat{x}_j^{(q)} \end{bmatrix} \in \mathbb{R}^n$ with $x_j^{(k)} \in \mathbb{R}^{nk}$, $k = 1, ...q, z_j = \begin{bmatrix} z_j^{(1)} \\ \vdots \\ z_j^{(q)} \end{bmatrix} \in \mathbb{R}^{qn_1}$ with $z_j^{(k)} \in \mathbb{R}^{\phi_1}$ and A is the $qn_1 \times qn_1$ anti-shift matrix, i.e.

$$\begin{aligned} A &= \begin{bmatrix} 0_{n1} & I_{n1} & 0_{n1} & 0_{n1} \\ \vdots & \ddots & \ddots & 0_{n1} \\ 0_{n1} & \dots & \dots & I_{n1} \\ 0_{n1} & \dots & \dots & 0_{n1} \end{bmatrix} \\ C_{qn1}^T &= \begin{bmatrix} I_{n1} \\ 0_{n1} \\ \vdots \\ 0_{n1} \end{bmatrix} \end{aligned} \tag{7}$$

The terms δ and $h > 0$ are positive real design paramaters and finally, $K(t)$ is the following diagonal matrix

$$K(t) = diag(PC^T) \triangleq diag(K^{(1)}(t)......K^{(q)}(t)) \tag{8}$$

where each $K^{(i)}$ is $n_i \times n_1$ matrix and P is $n \times n$ symmetric matrix governed by the following Riccati ODE (with $F(u, \hat{x}_j) = F(\cdot)$)

$$\begin{aligned} \dot{P} &= h(P + F(\cdot)P + PF^T(\cdot)) - PC^T CP) \\ P(0) &= P^T(0) > 0 \end{aligned} \tag{9}$$

The reader can analyse the stability test of the robust observer above [22]. This model is analysed in the case of two dimensions as is the problem to be solved in this work.

B. Neuronal Sliding Mode Control

This section deals with the design of a sliding mode controller via neural network: The Radial Basis Function Neural Network (RBF) can estimate any nonlinear function on a compact set with arbitrary accuracy, according to previous research on the universal approximation theorem [28]. The Lyapunov synthesis technique is used to construct a control algorithm based on the RBF model. The stability study of the proposed control algorithm is presented. The RBF network is used to estimate the unknown part of the dynamic equation of the manipulator. The sliding mode control can also be adjusted to the approximation error and the perturbation, together with the state estimation of FHGO.
Let the following system (4) be such that it describes in a reduced form the orientation of the Drone. In order to achieve longitudinal movements in space, it is feasible to have a robust orientation control, i.e., it is necessary to maintain an orientation of the reference variable $x_{j,ref} = x_{ref,j}$. Thus, that the control error can be compensated $e_j = x_{ref,j} - x_{1,j}$.

It is proposed the next sliding surface:

$$s = \dot{e}_j + k_1 e_j \tag{10}$$

Where $\dot{e}_j = \dot{x}_{j,ref} - \dot{\hat{x}}_j(t)$, we have the following for $k_1 > 0$:

$$s_j = \frac{de_j}{dt} + k_1 e_j \tag{11}$$

Therefore, if the sliding surface function is derived and the dynamics of the error is substituted $\ddot{e}_j = \ddot{x}_{ref,j} - \ddot{x}_{,j}$. Such that:

$$\dot{s}_j = \ddot{x}_{ref,j} - \ddot{x}_{,j} + k_1 \dot{e}_j \tag{12}$$

If $\ddot{x}_{j,ref} = \ddot{f}_j$ and $\ddot{x}_{j,ref} = \dot{f}_j$

$$\begin{aligned} \dot{s}_j &= -\alpha_j^{-1} u_j - \alpha_j^{-1} d_j(t) + k_1 \dot{e}_j + \ddot{f}_j \\ \dot{s}_j &= -\alpha_j^{-1} u_j - \mu_j(t) + k_1 \dot{e}_j + \ddot{f}_j \end{aligned} \tag{13}$$

We proposed $\alpha_j^{-1} d_j(t) = \mu_j(t)$ Since it is possible to have an uncertainty in the knowledge of the constants of the inertia matrix and also uncertain functions.It is proposed to estimate this function by means of a neuronal network $\hat{\mu}_j(t)$. Neural networks can estimate functions, but for this, network weights must be estimated. RBF networks are adaptively used to approximate the uncertain function $\mu_j(t)$. The algorithm are based on function (RBF) networks, in base on [28], [29]. Therefore, we have the following:

$$\hat{\mu}_j(t) = \hat{W}^T h(x) \tag{14}$$

whit:

$$h(x) = \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_n \end{bmatrix} \tag{15}$$

where $\hat{W} \in \mathbb{R}^n$ is the vector of estimated network weights, such that $h_j = \frac{g}{b_j^2}(\|x_p - c_{p,s}\|^2)$, where p is the the input of RBF and s is number hidded layer.

If we therefore occupy Reaching law on the sliding surface and separate the control law. With the above, the robust control in precense of the estimation with the neronal network and the FHGO observer we obtain the following:

$$u_j = -\alpha_j(-k_2 sgn(s_j) + \hat{\mu}_j(t) - k_1 \dot{\hat{e}}_j(t) - \ddot{f}_j) \tag{16}$$

Where, estimated variable via the FHGO observer shown above has to be used $\dot{\hat{e}}_j = -\dot{\hat{x}}$

Note 2 The estimation of the unknown function generates an error ϵ_W, such that when the estimation of this ϵ tends to zero.

$$\begin{aligned} \tilde{\mu}_j(t) &= \mu_j(t) - \hat{\mu}_j(t) \\ \tilde{\mu}_j(t) &= W^T h(x) + \epsilon_W - \hat{W}^T h(x) \\ \tilde{\mu}_j(t) &= \tilde{W}^T h(x) + \epsilon_W \end{aligned} \tag{17}$$

And Velocity variable is not available, therefore exist a error estimated velocity ϵ_o via FHGO , such that:

$$\begin{aligned} \epsilon_o &= \dot{x}_j(t) - \dot{\hat{x}}_j(t) \\ \dot{\hat{x}}_j(t) &= \dot{x}_j(t) - \epsilon_o \end{aligned} \tag{18}$$

For the design of the neuronal estimation (14) and the state estimation (6), it is known that these errors tend to zero as a function of their design, such that;

$$|\epsilon_o, \epsilon_W| \to 0 \forall t \to \infty \tag{19}$$

With the above, the following theorem is proposed

Theorem Having a quadrotor model with uncoupled dynamics shown in (4), and assumptions 1,2,3 are satisfied adn a estimatig of $\dot{\hat{x}}_j(t)$ via to FGHO shows in (6). The output controller (16) is said to be stable for gains $k_2 >> \epsilon_W - k_1 \epsilon_o$ and law of weight adaptation of the neural network:

$$\dot{\hat{W}} = -(\alpha_j)(s)h(x). \tag{20}$$

Proof: In this article, we employ a traditional method of evaluating the convergence of an adaptive controller, namely, we use the convergence features of the neuronal estimator in conjunction with the controller's convergence test, as proven and used in [29]. To prove this we will use Lyapunov convergence functions, which are proposed in the following:

$$V = 0.5 s_j^2 + 0.5 \alpha^{-1} \tilde{W}^T \tilde{W}$$

If we obtain the derivative under the trajectories of the system and substitute the dynamics of the sliding function (13), and robust control (16), we obtain:

$$\begin{aligned} \dot{V} &= s_j(\dot{s}_j) + \alpha^{-1} \tilde{W}^T \dot{\tilde{W}} \\ \dot{V} &= s_j(-\alpha_j^{-1} u_j - \mu_j(t) + k_1 \dot{e}_j) + \alpha^{-1} \tilde{W}^T \dot{\tilde{W}} \\ u_j &= \alpha_j k_2 sgn(s_j) - \alpha_j \hat{\mu}_j(t) + \alpha_j k_1 \dot{\hat{e}}_j(t) \end{aligned} \tag{21}$$

Thus:

$$\dot{V} = s_j(-k_2 sgn(s_j) + \hat{\mu}_j(t) - k_1\dot{\hat{e}}_j(t) - \mu_j(t) + k_1\dot{e}_j) + \alpha^{-1}\tilde{W}^T\dot{\tilde{W}}$$
$$\dot{V} = s_j(-k_2 sgn(s_j) - \tilde{\mu}_j(t) - k_1\epsilon_o) + \alpha^{-1}\tilde{W}^T\dot{\tilde{W}}$$
$$\dot{V} = s_j(-k_2 sgn(s_j) - \tilde{W}^T h(x) + \epsilon_W - k_1\epsilon_o) - \alpha^{-1}\tilde{W}^T\dot{\hat{W}}$$
$$\dot{V} = -\tilde{W}^T(sh(x) + \alpha^{-1}\dot{\hat{W}}) - s(-k_2 sgn(s_j) + \epsilon_W - k_1\epsilon_o) \tag{22}$$

with adaptive rule, this algorithm is stable and converged, this proof may be find [29], such that: $\dot{\hat{W}} = -(\alpha_j)(s)h(x)$.

$$\dot{V} \leq -|s|(\epsilon_W - k_1\epsilon_o) - |s|k_2$$
$$k_2 > \epsilon_W - k_1\epsilon_o \tag{23}$$

Therefore, the system is stable ■

IV. Numericall Results

According to recent basic conclusions presented in [27], the output feedback control design may be carried out under the blessing of the separation principle by cautiously integrating the state feedback controller (16) with the high gain observer (6). The state feedback controller's missing state variables are simply replaced by estimates supplied by the high gain observer and RBF neuroanl network in the output feedback controller. A comparable simulation framework was constructed around a physical model of a UVA quadrotor (4) and a realistic wind model to assess the effectiveness of the proposed high-gain observer, RBF network, and output feedback control system. Expressly, the model's initial values are set to zero, and the inertial matrix's value is JJ. The considered disturbance model is formed by the following formulations of the disturbance components. As a result for (4) the following wind disturbance is proposed [29]:

$$\xi_\theta(t) = 3sin(0.1t) + 2cos(3t+2) + 5sin(0.5t+2) + 0.1cos(10t) + cos(0.9t+2)$$
$$d_\theta = 0.1sin(0.1t)\xi_\theta(t)$$
$$\mu_\theta = \alpha_\theta^{-1}d_\theta \tag{24}$$

We propose control of the Euler Pitch angle, thus keeping the other two constants. We propose a following sinusoidal trajectory to give a training period to the RBF neural network of 2 inputs and 5 hided lawyer of (20) and (14) . It is proposed 30 seconds of experiment on Matlab-Simulink ambience. Dormand-Price ODE 45 is used whit $k_1 = 10, k_2 = 1$ *and* $k_3 = 10$. The estimating FGHO is $\delta, h = 1$.

$$\dot{s}_j = \ddot{x}_{ref,\theta} - \ddot{x}_{,\theta} + k_1\dot{e}_\theta \tag{25}$$

$$u_\theta = -\alpha_\theta(-k_2 sgn(s_\theta) + \hat{\mu}_\theta(t) - k_1\dot{\hat{e}}_\theta(t)) \tag{26}$$

Whit

$$\dot{\hat{x}}_\theta = F(u_\theta,\hat{x}_\theta)\hat{x}_\theta + \varphi(u_\theta,\hat{x}_\theta) - hK(t)z(t)$$
$$\dot{z}_\theta = \delta h(-z_\theta(t) + hA^T z(t)) + C_{qn1}^T(C\hat{x}_\theta - y_\theta) \tag{27}$$
$$z(0) = 0$$

It has been demonstrated in works such as [24] that the FHGO outperforms other traditional approaches for estimating the perturbation rate; in our study, we depend on this fact, thus only the FHGO is simulated.

A. Analysis of results

As can be seen in the results Fig (6), the neural network (14) has a good performance in estimating the wind perturbation since it achieves an oscillating error within a convergence ball, as shown in the following figure (6) :

Likewise, the FHGO observer 27 shows a great performance in estimate on noise presence precision in the signal of $x_{theta}(t)$, as shown in the following graphical result (Figure 7). Even though the system is in the presence of such aggressive wind and disturbances as those shown in figure (2), the system maintains a remarkable tracking performance shown in figure (3), this by using the robust controller shows in Figure (4). Moreover, with all of the above, the sliding surface figure (5) remains bounded even in the presence of noise, state estimation, and use of the neural network, without the need to increase the gain k_i of the controller (26) significantly.

V. Conclusion

The goal of this research was to investigate the robust control of a quadrotor helicopter's orientation by adequately combining the principles of neural networks, sliding modes, and state feedback through high gain observers, all while considering the separation criteria. This enables a robust controller-regulator with output feedback for suitable wind vectors and model uncertainty adjustment. The disturbance and angular velocity variables are correctly estimated by the observer and neural network, respectively, and these signals are used to compute a robust control signal based on sliding modes. Finally, the suggested controller's efficacy is proven in a simulation framework that incorporates a realistic physical model and is open for online testing on an open flight terminal.

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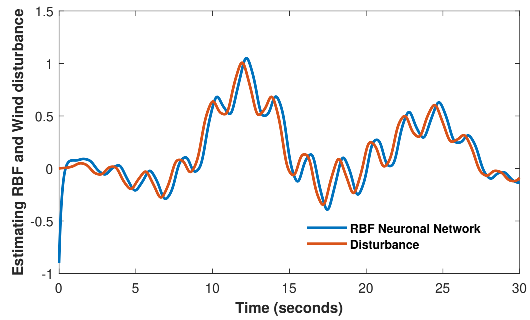

Fig. 2. Disturbance and wind dynamics followed in this work (24). These dynamics are compared with the estimation of the RBF (14).

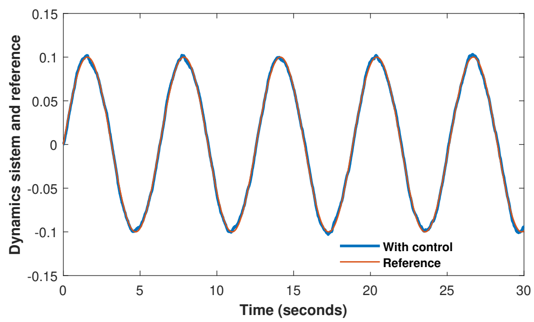

Fig. 3. Quadrotor dynamics in Pitch and expected reference (14).

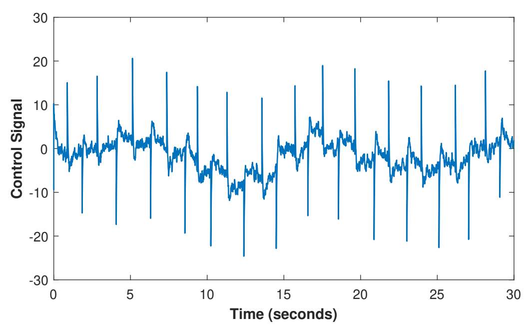

Fig. 4. Robust control dynamics (26) applied to the system (4)).

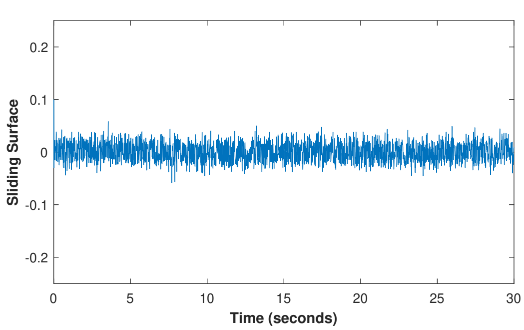

Fig. 5. Dynamics of the sliding surface in the presence of perturbations (25).

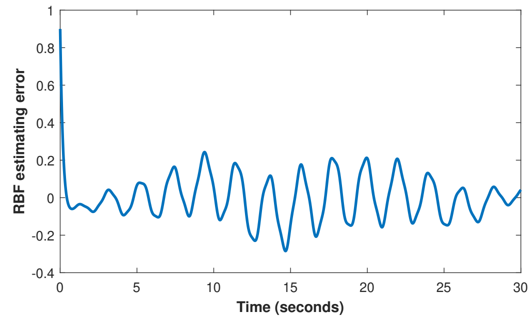

Fig. 6. Dynamics of disturbance estimation error based on the neural network (14).

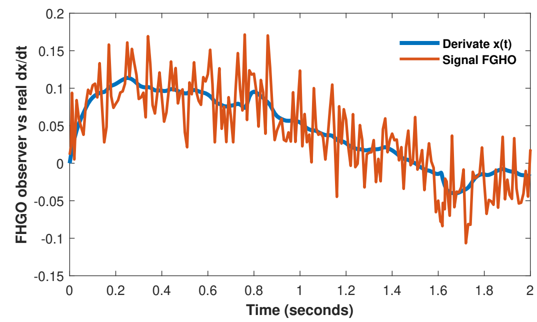

Fig. 7. Speed estimation via the FHGO (27), a time lapse of 2 seconds is shown in order to appreciate the estimation.

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