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IFAC PapersOnLine 55-22 (2022) 13–18

Quadrotor Composite Learning Neural Control with Disturbance Observer against Aerodynamic Disturbances

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Abstract: In this paper, a neural controller with disturbance observer is presented, in order to control a quadrotor Unmanned Aerial Vehicle (UAV) subject to aerodynamic disturbances. As a novel feature, the controller is formulated in a way to be implemented directly to a second-order system, such as the one of the quadrotor. Feedforward neural networks are employed in the control system design to compensate for internal disturbances, while the external disturbances and approximation error of the neural network are estimated by a disturbance observer. Moreover, composite learning is used to improve the overall performance, by estimating the state variables in real-time and using the estimation error in the updating rules of both the controller and the disturbance observer. An accurate disturbance modeling for the quadrotor is given, which considers wind and attitude changes, in order to evaluate the effectiveness of the controller. The controller successfully fulfills the task of trajectory tracking in the presence of wind and measurement noises, proving itself to be robust.

Keywords: Quadrotor UAV, Neural Networks, Adaptive control, Composite learning, Disturbance observer

1. INTRODUCTION

In recent years, Neural Networks (NN) became very popular in control system design within the advancements in intelligent control systems. An intelligent system could be defined as a system that is capable to achieve a previously defined task efficiently in an autonomous way. Neural Networks are naturally effective for this purpose due to their universal approximation property, indeed they can approximate any well-defined nonlinear function to any degree of accuracy, given adequate learning and a sufficient number of neurons, see Hornik et al. (1989). This is particularly useful in nonlinear control, since they could be used to estimate both model dynamics and disturbances, without any prior knowledge of the system.

Quadrotors are one type of Unmanned Aerial Vehicle (UAV) which have a large number of useful applications, such as search and rescue, precision agriculture, disaster management, aerial photography, etc. Consequently, their use increase exponentially in the last decade, mostly thanks to progress in microelectronics, being used in the industries and being accessible to people even with a limited budget. Their success is due to numerous reasons: they are mechanically quite simple, and therefore easy to be built and maintained, highly maneuverable, and very versatile, due to their size and Vertical Take Off and Landing (VTOL) characteristic.

From the control point of view, they possess four rotors at the four corners of a frame, which make them under-actuated, indeed four rotor thrusts control six degrees of freedom, and the dynamics are highly nonlinear.

Therefore, Neural Networks could be perfect candidates to work on such systems. In this paper, an adaptive controller which employs both Neural Networks and Disturbance Observer (DO) is introduced. This kind of controller is directly designed for a second-order system, for the first time.

The basic method to implement Neural Networks in a control system is through Feedback Error Learning (FEL). Considering the universal approximation property of NNs, model uncertainties could be satisfactorily estimated by NN with a bounded estimation error. However, the issue arises from the fact that external disturbances are typically an explicit function of time (not the system states), therefore it is not possible to estimate them using a NN as a function of system states. Further, although the controller design using NNs as an explicit function of time (e.g., with time-dependent weight matrices or time-dependent structure) could be an appropriate choice in this condition, the stability analysis of such systems is quite complex.

Motivated by this observation, the idea is to design a controller employing both NN and an adaptive DO in such

10.1016/j.ifacol.2023.03.003

a way that the NN deals with model uncertainties (internal disturbances), the function of states and inputs, and the DO with the external disturbances, the function of time, and with the estimation error of the Neural Network.

Different learning techniques could also be implemented to improve the overall performance, such as Composite Learning (CL), which, by employing a state observer, incorporates the estimation error in the updating law of the NN, leading to higher learning speed and higher accuracy, see Xu et al. (2019).

Accordingly, an adaptive control system will be developed in the current work for a 6-DOF quadrotor UAV with guaranteed stability in the presence of model uncertainties and external disturbances. The main contributions of this research are summarized as follows: a) An adaptive controller is designed directly for a second-order system that can deal with both model uncertainties and external disturbances with bounded tracking error. b) Using the proposed combination of NN + DO, the controller can effectively compensate for both time-dependent and state-dependent uncertain dynamics. c) The employment of the introduced composite learning scheme in the updating rules of both the NN and DO enhances learning efficiency.

Therefore, in this paper, firstly the dynamic model of the quadrotor is going to be introduced. Then, the aerodynamic disturbance acting on the quadrotor will be carefully modeled, in order to implement a realistic simulator. Subsequently, the controller design process along with the guidance loop design would be given in detail. Finally, simulation results are presented to prove the effectiveness of the designed controller.

2. MATHEMATICAL MODEL

2.1 Dynamic Model of the Quadrotor

The dynamic model of the system, using the small angle approximation, can be formulated in the inertial coordinates as a second order system (Emami and Banazadeh, 2020):

$$\begin{bmatrix}\ddot{x}\\ \ddot{y}\\ \ddot{z}\end{bmatrix} = \begin{bmatrix}0\\0\\-g\end{bmatrix} + \frac{T}{m}\begin{bmatrix}\cos\phi\sin\theta\cos\psi+\sin\phi\sin\psi\\ \cos\phi\sin\theta\sin\psi-\sin\phi\cos\psi\\ \cos\phi\cos\theta\end{bmatrix} + \frac{1}{m}Rf_D, \tag{1}$$

$$\begin{bmatrix}\ddot{\phi}\\ \ddot{\theta}\\ \ddot{\psi}\end{bmatrix} = \begin{bmatrix}\dot{\theta}\dot{\psi}(\frac{I_{yy}-I_{zz}}{I_{xx}})\\ \dot{\phi}\dot{\psi}(\frac{I_{zz}-I_{xx}}{I_{yy}})\\ \dot{\theta}\dot{\phi}(\frac{I_{xx}-I_{yy}}{I_{zz}})\end{bmatrix} + \begin{bmatrix}\frac{1}{I_{xx}}\tau_\phi\\ \frac{1}{I_{yy}}\tau_\theta\\ \frac{1}{I_{zz}}\tau_\psi\end{bmatrix} + \tau_D, \tag{2}$$

where g is the gravity acceleration, m the mass of the quadrotor, T is the total force directed along the vertical direction in body coordinates, in practice the lift provided by the rotors, $\tau_\phi, \tau_\theta, \tau_\psi$ the moments around the respective axes, I_{xx}, I_{yy}, I_{zz} the diagonal terms of the inertia matrix.

The disturbances in the model are introduced through the lumped terms $f_D \in R^3$ and $\tau_D \in R^3$, respectively force and torque, following the definition of Jeon et al. (2021). The rotation matrix from the body to inertial coordinates is defined as

$$R = \begin{bmatrix}\cos\psi\cos\theta & \cos\psi\sin\theta\sin\phi-\sin\psi\cos\phi & \cos\psi\sin\theta\cos\phi+\sin\psi\sin\phi\\ \sin\psi\cos\theta & \sin\psi\sin\theta\sin\phi+\cos\psi\cos\phi & \sin\psi\sin\theta\cos\phi-\cos\psi\sin\phi\\ -\sin\theta & \cos\theta\sin\phi & \cos\theta\cos\phi\end{bmatrix}. \tag{3}$$

The map to the four rotor thrusts is defined as

$$\begin{bmatrix}T\\ \tau_\phi\\ \tau_\theta\\ \tau_\psi\end{bmatrix} = \begin{bmatrix}1 & 1 & 1 & 1\\ 0 & l & 0 & -l\\ -l & 0 & l & 0\\ k_m & -k_m & k_m & -k_m\end{bmatrix}\begin{bmatrix}T_1\\ T_2\\ T_3\\ T_4,\end{bmatrix} \tag{4}$$

where T_i is the thrust provided by the $i-th$ rotor, for $i = 1, 2, 3, 4$, k_m is a positive constant and l is the arm of the rotor.

2.2 Dynamic model of disturbances

The goal of this work was to use a very accurate model of disturbances, which can comprise different physical effects, in order to present a realistic model and assess the performance of the controller in a true context.

Since the wind plays an important role in the aerodynamic disturbance, it is needed to define the relative velocity of the quadrotor center of mass, it is done as

$$V_r = R^T(W - V_I), \tag{5}$$

where $W = [W_x, W_y, W_z]^T$ is the wind velocity in inertial coordinates and V_I is the velocity in inertial coordinates, i.e. $V_I = [\dot{x}, \dot{y}, \dot{z}]^T$. Therefore, V_r is defined in the body frame. The relative velocity is assumed to be equal in all the area of each rotor, regarded as a disk.

Subsequently, the relative velocity with respect to each rotor is given by

$$\begin{aligned} V_1 &= -l\hat{\Omega}e_1 + V_r,\\ V_2 &= -l\hat{\Omega}e_2 + V_r,\\ V_3 &= l\hat{\Omega}e_1 + V_r,\\ V_4 &= l\hat{\Omega}e_2 + V_r, \end{aligned} \tag{6}$$

where $e_1 = [1\ 0\ 0]^T$ and $e_2 = [0\ 1\ 0]^T$ select the entries of the skew matrix $\hat{\Omega}$, expressed as

$$\hat{\Omega} = \begin{bmatrix}0 & -\Omega_3 & \Omega_2\\ \Omega_3 & 0 & -\Omega_1\\ -\Omega_2 & \Omega_1 & 0\end{bmatrix}, \tag{7}$$

where $\Omega_1, \Omega_2, \Omega_3$ are the rotational velocities in body axes.

The relative velocities to each rotor can be represented shortly with the notation

$$V_{i,j} = V_i^T e_j. \tag{8}$$

These relative velocities can then be split into the two perpendicular vectors:

$$V_{z,i} = \begin{bmatrix} 0 \\ 0 \\ V_{i,3} \end{bmatrix}, \; V_{h,i} = \begin{bmatrix} V_{i,1} \\ V_{i,2} \\ 0 \end{bmatrix}. \tag{9}$$

It is notable that $V_{z,i}$ is directed toward the vertical axis in the body frame, while $V_{h,i}$ lies in the horizontal plane.

The vertical force T_i acting on the $i-th$ rotor, i.e. the thrust produced, is generally defined by

$$T_i = k_\omega \omega_i^2, \tag{10}$$

where k_ω is a positive constant and ω_i is the rotational velocity of the rotor.

Therefore, the horizontal force H, acting on the rotor, is given by

$$H_i = cT_i V_{h,i}, \tag{11}$$

where c is a positive constant. This representation considers blade flapping, induced drag, and translation drag, under the assumption of slow speed, see Allibert et al. (2014).

The disturbance-induced torque can be modeled as

$$\begin{aligned} \tau_{D,1} &= \begin{bmatrix} l \\ 0 \\ d \end{bmatrix} \times H_1, \qquad \tau_{D,2} = \begin{bmatrix} 0 \\ l \\ d \end{bmatrix} \times H_2, \\ \tau_{D,3} &= \begin{bmatrix} -l \\ 0 \\ d \end{bmatrix} \times H_3, \quad \tau_{D,4} = \begin{bmatrix} 0 \\ -l \\ d \end{bmatrix} \times H_4, \end{aligned} \tag{12}$$

where d is the height of the rotor with respect to the body frame origin. To be able also to land, the ground effect needs to be taken into consideration. Due to the reduction in induced velocity close to the ground, the rotors work with better efficiency. Hence, during landing, the thrust which has to be provided by the propellers is smaller than in hovering. To model this phenomenon there are multiple ways. Here it is used the classic empirical formulation, provided by Council et al. (1957)

$$T_{IGE} = T_{OGE} \frac{1}{1 - \frac{r^2}{16z^2}}, \tag{13}$$

where T_{IGE} and T_{OGE} are respectively the total thrust in ground effect and out of ground effect, r the total rotor radius. Indeed, when touching the ground, the parameter z in (13) will reach a minimum of d and not 0, avoiding a possible numerical issue.

Subsequently, the ground effect can be added in the formulation of the vertical disturbance and of the torque generated around ϕ and θ. It is done through the ratio $K_g = \frac{T_{IGE}}{T_{OGE}}$ which is larger than 1 in ground effect.

Thus, the lumped disturbance force can be written as $f_D = \sum_{i=1}^{4} H_i$ which can be reshaped, combining previous equations and adding ground effect, into

$$f_D = cT \begin{bmatrix} V_r^T e_1 \\ V_r^T e_2 \\ 0 \end{bmatrix} + cl\Omega_3 \begin{bmatrix} T_2 - T_4 \\ T_3 - T_1 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ K_g T \end{bmatrix}, \tag{14}$$

where $K_g = \frac{T_{IGE}}{T_{OGE}}$.

Developing (12), the total torque τ_D can be expressed as

$$\begin{aligned} \tau_D = & K_g dcT \begin{bmatrix} -V_r^T e_2 \\ V_r^T e_1 \\ 0 \end{bmatrix} + K_g dcl\Omega_3 \begin{bmatrix} T_1 - T_3 \\ T_2 - T_4 \\ 0 \end{bmatrix} + \\ & + cl \begin{bmatrix} 0 \\ 0 \\ T_1 V_{1,2} - T_2 V_{2,1} - T_3 V_{3,2} + T_4 V_{4,1} \end{bmatrix}. \end{aligned} \tag{15}$$

It has to be pointed out that when $W = 0$ the disturbance terms do not become zero. This is due to the fact that they take into account the rotation and attitude changes of the quadrotor.

In this kind of modeling, parasitic drag was neglected, but it would be interesting to investigate its influence in future work.

3. CONTROLLER DESIGN

The adaptive controller which employs both neural networks and disturbance observer is now introduced. It has to be remarked again that the controller acts directly on the second order system, in an original way. Therefore, assume that the dynamic model of the system is given in the following form Emami et al. (2022):

$$\ddot{\xi} = F(\xi) + B(\xi)u + \Delta(\xi, u) + \bar{D}(t), \tag{16}$$

where $\Delta(\xi, u)$ and $\bar{D}(t)$ are the previously discussed internal and external disturbances.

In order to have the inverse of matrix B, the system is assumed squared, i.e. $dim(\xi) = dim(u) = n$, where $\xi = [z, \phi, \theta, \psi]^T$ and $u = [T_1, T_2, T_3, T_4]^T$. Since the four rotors can control only four degrees of freedom, the remaining x, y are going to be regarded in the guidance loop.

Similar to the sliding mode approach, a filtered tracking error is defined as

$$s = \dot{e} + \lambda_1 e + \lambda_2 \int e dt, \tag{17}$$

where λ_1 and λ_2 denotes positive-definite matrices, and

$$e = \xi - \xi_{des}, \tag{18}$$

is the tracking error. The derivative of s can be computed as

$$\begin{aligned} \dot{s} &= \ddot{e} + \lambda_1 \dot{e} + \lambda_2 e \\ &= F(\xi) + B(\xi)u + \Delta + \bar{D} - \ddot{\xi}_{des} + \lambda_1 \dot{e} + \lambda_2 e. \end{aligned} \tag{19}$$

In addition, considering a state observer with $\hat{\xi}$ as its state vector, the estimation error e_D is defined as

$$e_D = \hat{\xi} - \xi, \quad (20)$$

and therefore, the filtered estimation error would be defined as follows:

$$s_D = \dot{e}_D + \lambda_1 e_D + \lambda_2 \int e_D dt. \quad (21)$$

Accordingly, the novel second-order observer model is described by

$$\ddot{\hat{\xi}} = F(\xi)+B(\xi)u+\hat{\Delta}(\xi,u)+\hat{D}-k_1 s_D-\lambda_1\dot{e}_D-\lambda_2 e_D, \quad (22)$$

where k_1 is a positive constant, Δ and $\hat{\Delta}$ defined as

$$\Delta = {W^*}^T \mu(\xi,u) + \epsilon, \ \hat{\Delta} = \hat{W}^T \mu(\xi,u), \quad (23)$$

are, respectively, the ideal model and the approximation provided by the NN, ϵ denotes the estimation error of the NN. Here, W^*, $\hat{W}$, and $\mu(\xi,u)$ represent the optimal weight matrix, the estimated weight matrix, and an appropriate basis function vector, respectively. Such a formulation in which only the output weight matrix W is updated during the training process is known as an Extreme Learning Machine (ELM) that can satisfy the universal approximation property with a reduced computational burden. In addition, D is the disturbance term which has to be estimated by the observer, so that

$$D(t) = \bar{D}(t) + \epsilon, \quad (24)$$

in order to compensate for both the external disturbances and the approximation error of the NN, accordingly, $\hat{D}$ is the estimation.

Thus, the control command can be defined as

$$u = B(\xi)^{-1}[\ddot{\xi}_{des} - \lambda_1\dot{e} - \lambda_2 e - k_1 s - F(\xi) - \hat{\Delta} - \hat{D}]. \quad (25)$$

In this regard, using the following updating rules,

$$\dot{\hat{W}} = \Gamma[\mu(k_2 s^T - k_3 s_D^T) - \sigma_W \hat{W}], \quad (26)$$

$$\dot{\hat{D}} = (k_2 s - k_3 s_D) - k_4(\dot{s}_D + k_1 s_D), \quad (27)$$

with k_is denoting positive constants and σ_W being the sigma modification term, it is possible to prove that both tracking error and estimation error are uniformly ultimately bounded, while the proof is omitted for brevity.

It is worth mentioning that, although $\dot{s}_D$ is employed in (27), there is no need to compute it. More precisely, by defining an auxiliary variable η defined as

$$\dot{\eta} = k_2 s - k_3 s_D - k_4 k_1 s_D, \quad (28)$$

the estimated disturbance term $\hat{D}$ can be computed as

$$\hat{D} = \eta - k_4 s_D. \quad (29)$$

It has to be remarked that the controller does not need any prior information about the disturbances. Besides, it should be noted that the employment of the abovementioned composite learning scheme in (26) and (27) can effectively enhance the learning process, thereby eliminating the requirement for high learning rates, which may cause different practical issues in real applications.

Therefore, the novelty of the article was to design a *composite learning* neural (disturbance observer-based) controller for a *second-order* system.

3.1 Guidance loop

Since the state variables were defined as z, ϕ, θ, ψ but the task of the controller could be to track a reference trajectory, defined by the position x, y, z, it is needed to extract a formulation to relate x and y to the desired state variables, in particular, ϕ and θ.

The two equations of the dynamics can be written as

$$\begin{bmatrix}\ddot{x}\\ \ddot{y}\end{bmatrix} = -\frac{T}{m}\begin{bmatrix}\cos\psi & \sin\psi\\ \sin\psi & -\cos\psi\end{bmatrix}\begin{bmatrix}\cos\phi\sin\theta\\ \sin\phi\end{bmatrix}, \quad (30)$$

from which it is possible to derive

$$\begin{bmatrix}\cos(\phi_{des})\sin(\theta_{des})\\ \sin(\phi_{des})\end{bmatrix} = -\frac{T}{m}\begin{bmatrix}\cos\psi & \sin\psi\\ \sin\psi & -\cos\psi\end{bmatrix}\begin{bmatrix}\ddot{x}_{des}\\ \ddot{y}_{des}\end{bmatrix}. \quad (31)$$

In the simulator implementation, the guidance loop was designed through a simple Proportional Derivative (PD) action.

The adaptive controller requires also to compute the first and the second derivatives of the desired state variables. Thus, it is computed the first and second derivative of (31), so that

$$\begin{aligned}\dot{\phi}_{des} &= \frac{m}{T\cos\phi_{des}} y_{des}^{iii},\\ \dot{\theta}_{des} &= (-\frac{m}{T}x_{des}^{iii} + \dot{\phi}_{des}\sin\phi_{des}\sin\theta_{des})/\cos\phi_{des}\cos\theta_{des},\end{aligned} \quad (32)$$

and

$$\begin{aligned}\ddot{\phi}_{des} =& (\frac{m}{T}y_{des}^{iv} + \sin\phi_{des}\dot{\phi}_{des}^2)/\cos\phi_{des},\\ \ddot{\theta}_{des} =& (\frac{m}{T}x_{des}^{iv} - \sin\phi_{des}\sin\theta_{des}\ddot{\phi}_{des}+\\ &- \dot{\phi}_{des}^2\cos\phi_{des}\sin\theta_{des}+\\ &- 2\dot{\phi}_{des}\dot{\theta}_{des}\cos\theta_{des}\sin\phi_{des}+\\ &- \dot{\theta}_{des}^2\cos\phi_{des}\sin\theta_{des})/(-\cos\phi_{des}\cos\theta_{des}),\end{aligned} \quad (33)$$

where the superscript iii and iv stand for the third and fourth derivatives, respectively. It is also made the assumption that $\psi \approx 0$ so that $\sin\psi = 0$ and $\cos\psi = 1$ and that $\dot{\psi} \approx 0$.

4. SIMULATION RESULTS

The full simulator and the adaptive controller were implemented on MATLAB Simulink and tested with extensive simulations, in different conditions and missions.

The quadrotor parameters used were chosen as shown in table 1.

Table 1. Quadrotor parameters

Parameter	Description	Value
m	mass	0.58 kg
l	arm lenght	0.25 m
d	rotor distance to CoG	0.0188 m
(I_{xx},I_{yy},I_{zz})	inertia moments	(0.01,0.01,0.02) $kg * m^2$
K_m	thrust factor	0.6059 m

The controller parameters were tuned as shown in table 2.

Table 2. Controller parameters

Parameter	Value
λ_1	diag[2.5,50,50,0.1]
λ_2	diag[0.875,10,10,0.0025]
k_1	200
Γ	60
σ_W	0.001
k_2	[50,50,50,50]
k_3	[20,20,20,20]
K_4	0.3 × [1,2,2,1]

Here for conciseness, only the results of three basic situations are presented. The case with no external disturbances, the case with wind, and finally the case with wind and measurement noise.

It was set to track the trajectory defined by the functions

$$x_{des} = \sin\left(\frac{1}{5}\pi t + \frac{\pi}{4}\right) + \frac{\sqrt{2}}{2}, \tag{34}$$

$$y_{des} = \sin\left(\frac{1}{5}\pi t + \pi\right), \tag{35}$$

for x and y and a landing manoeuvre, starting at $t = 10s$, at constant speed, for z, with $z_0 = 8m$. The results of the first case with no external disturbance could be considered ideal. The trajectory can be observed in Fig. 1 and the thrust inputs, needed to achieve it, in Fig. 2.

The controller performs very well and the total Root Mean Square Error (RMSE) on the trajectory is given in table 3.

Table 3. RMSE

Condition	Value
Ideal	0.04852
Wind	0.05168
Wind and noise	0.05476

The RMSE was defined as

$$RMSE = \sqrt{\frac{1}{T}\int_0^T e^T e \, dt}. \tag{36}$$

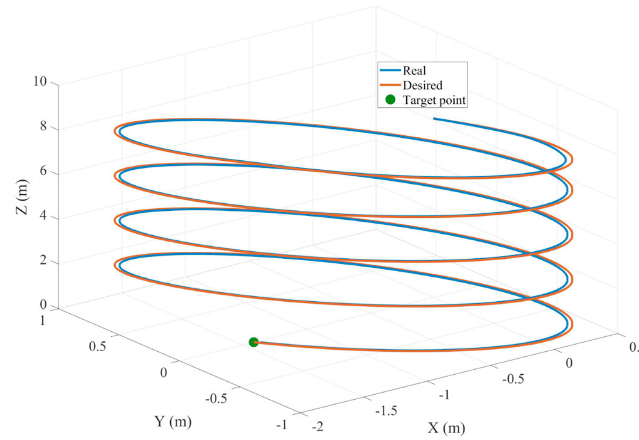

Fig. 1. Quadrotor trajectory in ideal case

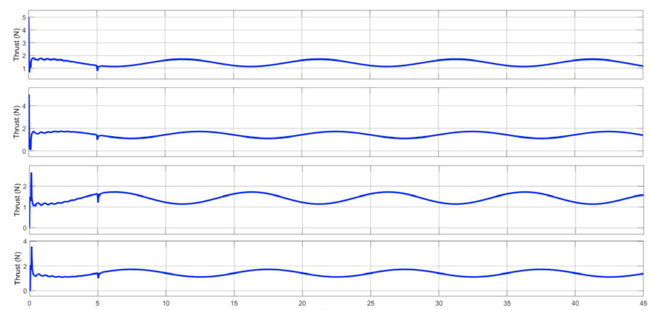

Fig. 2. Thrust inputs in ideal case

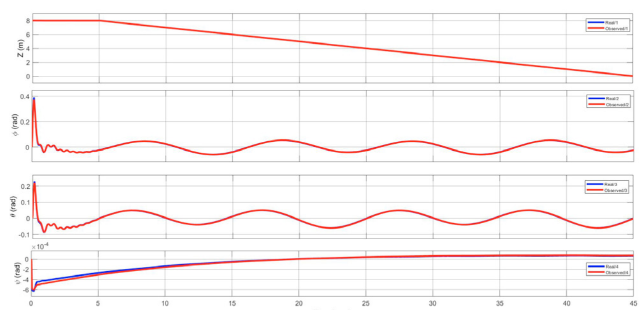

Fig. 3. State observer performance considering wind effects

The wind was then introduced in the model as

$$W_x = W_y = W_z = 0.2 \sin\left(\frac{1}{10}\pi t + \frac{\pi}{4}\right). \tag{37}$$

This formulation could represent wind shear, see Kang et al. (1992).

In this case, the capability of the observer to estimate the state variables can be inferred from Fig. 3. From Fig.4, it is also possible to see the determined control commands, which are feasible.

Then, in table 3 the increase in RMSE, due to the external disturbances, is quantified. The increase is slight, proving the effectiveness of the controller.

Finally, the more complete case, in which also measurement noises are taken into account, is considered. In the simulator, it was modeled as the band-limited white noise on the accelerations. The performance of the State observer is presented in Fig. 5.

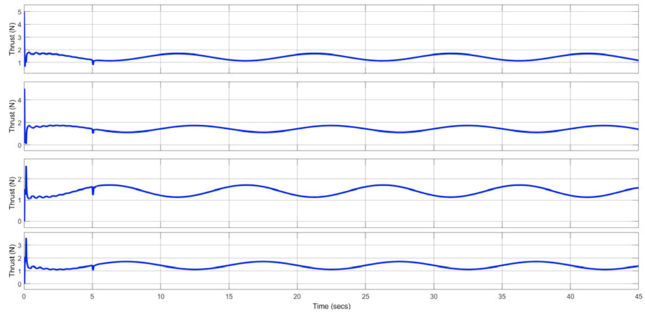

Fig. 4. Thrust inputs considering external disturbance

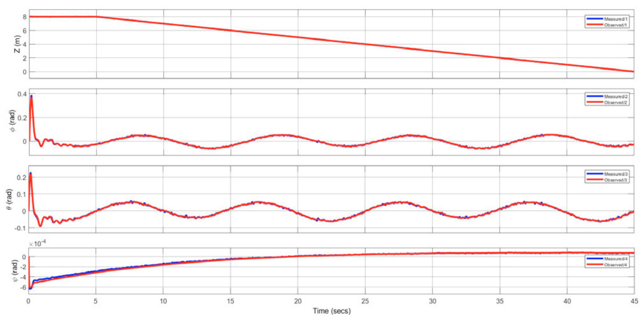

Fig. 5. State observer performance considering external disturbance and measurement noises

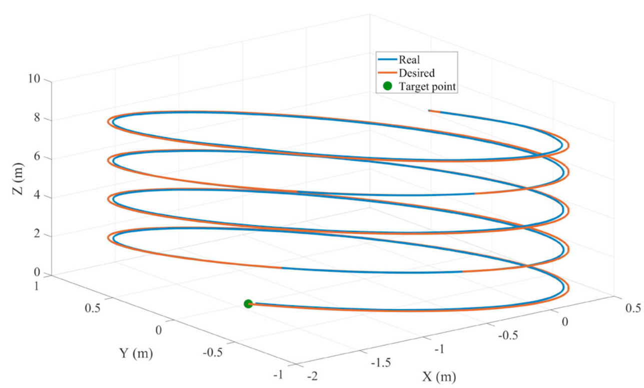

Fig. 6. Quadrotor trajectory considering external disturbances and measurement noises

The observer is still able to estimate the system states, quite satisfactorily. The achieved trajectory is shown in Fig. 6.

Not any decrease in quality can be noted from Fig. 6, with respect to Fig. 1. The inputs required are therefore shown in Fig. 7, a small scattering from the noise can be observed.

The final RMSE value can be seen in table 3. It is still very close to the ideal value proving again the controller to be robust.

5. CONCLUSION

An original neural controller with disturbance observer, trained with composite learning was presented. The controller was demonstrated to be effective against internal and external disturbances, in quadrotor control. The key point of this work, which was the design of an adaptive neural controller for a second-order system in a single-step

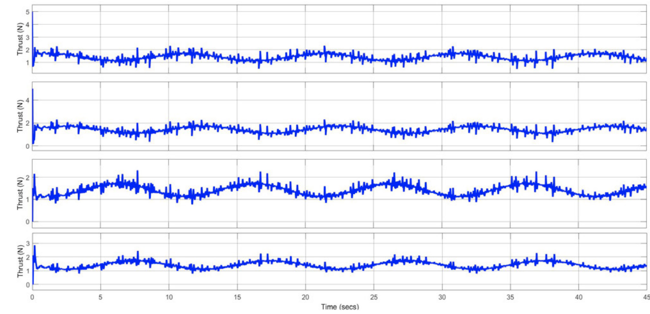

Fig. 7. Thrust inputs with external disturbance and measurement noise

approach, can be generalized in future studies to different types of aerial vehicles such as a reentry vehicle in the presence of significant model uncertainties and external disturbances. Future work would also consider a fault-tolerant control and include additional uncertain dynamics. Besides, the controller design could be extended by the full stability analysis.

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