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Adaptive Neural Network-based Nonlinear Fault-Tolerant Control of a Disturbed UAV

Olivier Baraka Mushage

Associate Professor, Faculty of Applied Sciences and Technologies, Université Libre des Pays des Grands Lacs

ABSTRACT:This paper addresses the control problem for a six degree of freedom quadrotor subject to perturbations such as multiple actuation failures, external disturbances and uncertain parameters. A nonlinear control law is designed so that it provides a continuous control signal that tackles simultaneously the aforementioned perturbations. Through a Lyapunov stability analysis, it is proved that, under the proposed control law, stability of the closed-loop system and achievement of the control objectives are guaranteed. To illustrate the efficiency of the proposed quadrotor's controller, simulation results are presented. The obtained results are compared to those obtained using a controller available in the literature. Thanks to these results, robustness, fast response and good tracking capability guaranteed by the proposed controller are demonstrated. Hence, with the proposed controller, increased safety and reliability are obtained for the aircraft's operations.

KEYWORDS: Quadrotor, actuator fault, adaptivenonlinear control, neural network, parametricuncertainty, external disturbances.

I.INTRODUCTION

Drones are becoming popular as they are increasinglyused in many applications such as environment exploration, military missions, traffic surveillance, rescue operations, structure inspection, mapping, aerial cinematography, parcel delivery, etc. [1-6]. Drones are multirotor Unmanned Aerial Vehicle (UAV) of different kindslike bi-rotor, tri-rotor,quadrotor, and conventional helicopter [3,6-8].Since several years, a tremendous effort has been devoted to developing control strategies for different kindsof UAVs, which are highly nonlinear under-actuatedsystems. These UAVs are often affected by various disturbances, which makes their control very challenging.To accomplish efficiently their missions, these UAVs require controllers that can tackle actuation faults, environmental disturbances such as wind, rain and physicalparameter changes such as variation of mass and inertia. UAVs can encounter loss of effectiveness (LOE)due to a motor’s fault or propeller’s damage or batterydrainage [2, 3]. A partial LOE in one of the motors orin more causes simultaneous loss of thrust and torque. The occurrence of such faults significantly degrades theperformance of the quadrotor. Fault-tolerant control(FTC) strategies are hence developed to accommodate such faults.Numerous papers proposing controllers for UAV swith perturbations have beenpublished. An FTC for aquadrotor has been presented in [7], which is based onthe combination of the traditional slidingmode control(SMC) technique with the interval type-2 fuzzy logiccontrol approach. The authors of [7] used the intervaltype-2 fuzzy system to cancel the chattering phenomenon, which is the main drawback of the SMC. However, the controller’s implementation requires theexact knowledge of the UAV’s parameters and the upper bound of a lumped disturbance. Robust controllersbased on asecondorder SMC (SOSMC) strategy fora quadrotor UAV were proposed in [1]. The controllerswere designed by considering separately a fully actuated subsystem and an underacted subsystem. A sliding manifoldthat linearly combines trackingerrors ontwo state variables and their derivatives was used forthe design of a controller for the underactuated subsystem. However, exact knowledge of system parametersis necessaryfor the controllers’ implementation. In [2],linear parametervarying (LPV) control technique wasused to develop an active FTC strategy for a quadrotor. In addition to actuation faults, perturbations suchas payload grasping and dropping caused variations ofsystem dynamics were addressed. The proposed FTCuses an LPV-based faultdetection and diagnosis (FDD)scheme that provides an estimated value of partial lossof effectiveness, which is used by the controller to compensate the effects of system parameters changes andactuationfaults. However, this FTC is designed usinga simplified linear model. Therefore, knowing that thequadrotor is a highly nonlinear system, the FTC controls it with limited accuracy. In addition, the use ofthe FDD increasescomputation burden and the riskof more tracking error in case inaccurate fault estimation.

Motivated by the above discussion, considering thatsafety and reliability are always a critical issue for aircraftapplications, this paper presents the design of anadaptive controller for a six degree of freedom quadrotor aircraft so thatsevere perturbations such as motors failures or rotor damages, unknown/uncertain parameters and external disturbancesare tackled. Thiscontroller is based on the nonlinear control approachintroduced in [9, 10] for strict-feedback nonlinearsystems and it uses radial basis function neural networks (RBFNN) for unknown dynamics approximation. Control signals generated are continuous so thatreal-world implementation can be possible with energyconsumption reduction. To design controllers for theposition subsystem, which is underactuated, virtual control inputsare designed for the $x$and $y$subsystem.

The paper is organized as follows: In section 2, thedynamic model for the quadrotor, is presented. Thecontrol problemis presented in section 3. Section 4 isdevoted to the control law design and the Lyapunov'sstability analysis for the controlled quadrotor by considering that its model is made of a set of coupled nonlinear subsystems. In section 5simulation results arepresented and discussed and a benchmark is presented.Section 6 concludes the paper.

II. QUADROTOR MODEL PRESENTATION

As aforementioned, a quadrotor UAV is a highly nonlinear, multivariable, and underactuated dynamic system.

Remark 1:Throughout all the paper, in order to alleviate notations, time varying quantities are written without theindependent variable $(\boldsymbol{t})$.

The complete dynamics that governs the quadrotor UAVcan be obtained using the Newton-Euler approach as follows [1, 11]:

$$\begin{cases} \ddot{x} = -\frac{k_1}{m_s}\dot{x} + \frac{1}{m_s}(\cos\phi\sin\theta\cos\psi + \sin\phi\sin\psi)u_1 \\ \ddot{y} = -\frac{k_2}{m_s}\dot{y} + \frac{1}{m_s}(\cos\phi\sin\theta\sin\psi - \sin\phi\cos\psi)u_1 \\ \ddot{z} = -g - \frac{k_3}{m_s}\dot{z} + \frac{1}{m_s}(\cos\phi\cos\psi)u_1 \\ \ddot{\phi} = qr\frac{I_y - I_z}{I_x} + \frac{J_r}{I_x}q\Omega_r - \frac{k_4}{I_x}lp + \frac{l}{I_x}u_2 \\ \ddot{\theta} = pr\frac{I_z - I_x}{I_y} - \frac{J_r}{I_y}p\Omega_r - \frac{k_5}{I_y}lq + \frac{l}{I_y}u_3 \\ \ddot{\psi} = pq\frac{I_x - I_y}{I_z} - \frac{k_6}{I_r}r + \frac{C}{I_z}u_4 \end{cases} \tag{1}$$

where:

- $[x, y, z]^T$is the quadrotor's center of gravity (COG)position vector in the earth-frame;
- $[\phi,\ \theta, \psi\ ]^T$is the vector of the three Euler's angles,which are the roll, the pitch and the yaw, respectively;
- $[p, q, r]^T$is the angular velocity vector in the bodyframe;
- $k_i > 0$, is the air drag coefficient in the ith degreeof freedom ($i\ =\ 1, 2, 3, 4, 5, 6$);
- $J_r$is the inertia of the z-axis;
- $g$is the acceleration of gravity;
- $l$is the distance from the center of each rotor to theCOG;
- C>0 is a proportional coefficient;
- I_x, I_yet $I_z$are the inertia of the quadrotor in thee_x, $e_y$and $e_z$axis, respectively;
- $u_1$is the total thrust on the body in the z- axis;
- u_2, $u_3$andu_4 are the roll torque, the pitch torqueand the yawing torque, respectively;
- $\Omega_r = -\Omega_1 + \Omega_2 - \Omega_3 + \Omega_4$is the overall residual rotorangular velocity with Ω_i being the angular velocity of the ith rotor ($1\ \le\ i\ \le\ 4$).

In Eq. (1), the terms$K_1\,\dot{x}/m_s$, $K_2\,\dot{y}/m_s$ and $K_3\,\dot{z}/m_s$represent air drag distribution in the $e_x, e_y$and $e_y$axis, respectively.

Assumption 1:*There is no singularity problem as theEuler's angles are bounded as follows: the roll angle,*$-\pi/2 < \phi < \pi/2$*; the pitch angle,*$-\pi/2 < \theta < \pi/2$*;and the yaw angle,*$-\pi < \psi < \pi$.

The angular velocity vector in the body frame is relatedto the Euler's angles as follows:

$$\begin{bmatrix} p \\ q \\ r \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi\sec\theta & \cos\phi\sec\theta \end{bmatrix} \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} \tag{2}$$

Assumption 2:*The quadrotor is considered being asymmetric rigid body.*

For each of the four rotors, the angular velocity $\Omega_i$isrelated to the control input u_i(for $1 \leq i \leq 4$) as follows:

$$\begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} = \begin{bmatrix} b & b & b & b \\ lb & 0 & -lb & 0 \\ 0 & -lb & 0 & lb \\ -k & k & -k & k \end{bmatrix} \begin{bmatrix} \Omega_1^2 \\ \Omega_2^2 \\ \Omega_3^2 \\ \Omega_4^2 \end{bmatrix} \quad (3)$$

where $k > \mathbf{0}$ and $b > \mathbf{0}$ are parameters depending on thedensity of air, the radius of the propellers, the number of blades, their geometry, and their lift and drag coefficients[1, 12].

The thrust generated by the ith (with $i = 1, 2, 3, 4$)rotor is given by:

$$F_i = b\Omega_i^2 \quad (4)$$

The thrusts Fi (with $i = 1, 2, 3, 4$) are considered as thereal control inputs to the dynamical system.The reactive torque caused by the rotor drag generated by the rotation of the ith rotor in free air is:

$$M_i = -k\Omega_i^2 \quad (5)$$

The rolling torque is provided by the difference between the first and third rotors' thrusts as follows:

$$M_\phi = l(F_1 - F_3) \quad (6)$$

The pitching torque is due to the difference between the trusts generated by the second and the fourth rotor asfollows:

$$M_\theta = l(F_4 - F_2) \quad (7)$$

The yawing torque generated by the four rotors is:

$$M_\psi = C(F_1 - F_2 + F_3 - F_4) \quad (8)$$

III. PROBLEM STATEMENT

Let us consider a quadrotor UAV with uncertain parameters (i.e. with modelling errors and/or random parameterschanges), external disturbances on the six degreesof freedom and actuation faults. Therefore, the UAV ismodelled as a set of the following subsystems:

(a) **The roll (ϕ), pitch (θ) and yaw (ψ) subsystem**

$$\begin{cases} \dot{\boldsymbol{X}}_{1,\phi,\theta,\psi} = \boldsymbol{X}_{2,\phi,\theta,\psi} \\ \dot{\boldsymbol{X}}_{2,\phi,\theta,\psi} = \boldsymbol{f}_{\phi,\theta,\psi}(X) + \boldsymbol{b}_{\phi,\theta,\psi}\boldsymbol{u}_{\phi,\theta,\psi} + \boldsymbol{d}_{\phi,\theta,\psi} \end{cases} \quad (9)$$

(b) **The $x$and y positions subsystem**

$$\begin{cases} \dot{\boldsymbol{X}}_{1,x,y} = \boldsymbol{X}_{2,x,y} \\ \dot{\boldsymbol{X}}_{2,x,y} = \boldsymbol{f}_{x,y}(\boldsymbol{X}) + \boldsymbol{b}_{x,y}\boldsymbol{u}_{x,y} + \boldsymbol{d}_{x,y} \end{cases} \quad (10)$$

(c) **The altitude (z) subsystem**

$$\begin{cases} \dot{x}_{11} = x_{12} \\ \dot{x}_{12} = a_{11}x_{12} - g + \frac{g_z(X)}{m_s}u_1 + d_z \end{cases} \quad (11)$$

where :

$$\boldsymbol{X} = [x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}]^T = [\phi, \dot{\phi}, \theta, \dot{\theta}, \psi, \dot{\psi}, x, \dot{x}, y, \dot{y}, z, \dot{z}]^T,$$

$$\boldsymbol{X}_{1,\phi,\theta,\psi} = [x_1, x_3, x_5]^{\boldsymbol{T}}, \dot{\boldsymbol{X}}_{2,\phi,\theta,\psi} = [x_2, x_4, x_6]^{\boldsymbol{T}}, \boldsymbol{X}_{1,x,y} = [x_7, x_9]^{\boldsymbol{T}}, \boldsymbol{X}_{2,x,y} = [x_8, x_{10}]^{\boldsymbol{T}},$$

$$\boldsymbol{f}_{x,y}(\boldsymbol{X}) = [a_9x_8, a_{10}x_9]^{\boldsymbol{T}}, \boldsymbol{f}_{\phi,\theta,\psi}(\boldsymbol{X}) = \begin{bmatrix} a_1qr + a_2q\Omega_r + a_3p \\ a_4pr + a_5p\Omega_r + a_6q \\ a_7pq + a_8r \end{bmatrix}, \boldsymbol{b}_{\phi,\theta,\psi} = \mathrm{diag}[b_1, b_2, b_3],$$

$\boldsymbol{b}_{x,y} = \text{diag}[1/m_s, 1/m_s]$, $\boldsymbol{u}_{\boldsymbol{\phi},\boldsymbol{\theta},\boldsymbol{\psi}} = [u_2, u_3, u_4]^T$, $\boldsymbol{u}_{\boldsymbol{x},\boldsymbol{y}} = [u_x, u_y]^T$, $a_1 = \frac{I_y - I_z}{I_x}$, $a_2 = \frac{J_r}{I_x}$, $a_3 = -\frac{k_4}{I_x} l$, $a_4 = \frac{I_z - I_x}{I_y}$, $a_5 = -\frac{J_r}{I_y}$, $a_6 = -\frac{k_5}{I_y}$, $a_7 = \frac{I_x - I_y}{I_x}$, $a_8 = -\frac{k_6}{I_z}$, $a_9 = -\frac{k_1}{m_s}$, $a_{10} = -\frac{k_2}{m_s}$, $a_{11} = -\frac{k_3}{m_s}$, $b_1 = \frac{l}{I_x}$, $b_2 = \frac{l}{I_y}$, $b_3 = \frac{c}{I_z}$, $g_z(\boldsymbol{X}) = \cos x_1 \cos x_3$, $u_x = \cos x_1 \sin x_3 \cos x_5 + \sin x_1 \sin x_5$, $u_y = \cos x_1 \sin x_3 \sin x_5 - \sin x_1 \cos x_5, d_j$ (with $j = x,, y, z, \phi, \theta, \psi$) is an unknown bounded external disturbance affecting the j movement and u_i(with $1 \le i \le 4$)is an actuator's output modelled as follows [9, 10, 13]:

$$u_i = (1 - g_{ia})u_{ia} + b_{ia}, \forall t \ge t_f \tag{12}$$

where u_{ia} is the ith actuator's input, $0 \le g_{ia} < 1$ is the degree to which the actuator's effectiveness is lost, $b_{ia}$is the biasfault and$t_f$is the unknown fault occurrencetime. Hence, the actuator's fault can be either a constant/time varying nonaffine fault (when$1 - g_{ia} \neq 0$),a bias fault (when $u_i = u_{ia} + b_{ia}$), a gain fault (when$u_i = (1 - g_{ia})u_{ia}$) or a complexfault corresponding tothe combination of all the aforementioned faults.The control objective is to apply suitable controlactions to the four rotors of the UAV such that thequadrotor remains stable while tracking$x_{1d}, x_{3d}, x_{5d}, x_{7d}, x_{9d}$and x_{11d}, which are the desired values for angles$\phi, \theta, \psi$and positions $x, y$and$z$, respectively. Thiscontrol objective should be achieved despite perturbations such as external disturbances, uncertain parameters and multiple actuation faults.

IV.DESIGN OF THE ADAPTIVE RBFNN-BASED FAULT-TOLERANT CONTROLLER

Let us define $\boldsymbol{e} = [\boldsymbol{e}_{\boldsymbol{\phi}}, \boldsymbol{e}_{\boldsymbol{\theta}}, \boldsymbol{e}_{\boldsymbol{\psi}}, \boldsymbol{e}_{\boldsymbol{x}}, \boldsymbol{e}_{\boldsymbol{y}}, \boldsymbol{e}_{\boldsymbol{z}}]^{\boldsymbol{T}}$as the trackingerror vector for the six subsystems with:

$$\begin{cases} e_\phi = x_1 - x_{1d} \\ e_\theta = x_3 - x_{3d} \\ e_\psi = x_5 - x_{5d} \\ e_x = x_7 - x_{7d} \\ e_y = x_9 - x_{9d} \\ e_z = x_{11} - x_{11d} \end{cases} \tag{13}$$

Let us defines$\boldsymbol{s} = [s_z, s_\phi, s_\theta, s_\psi, s_x, s_y]^T$as a vector of filtered errors functions, for the six subsystems,where:

$$s_j = \dot{e}_j + c_j e_j \tag{14}$$

with $c_j > 0$ and $j = \phi, \theta, \psi, x, y, z$.

The control law for the three aforementioned subsystems is designed as follows:

$$\boldsymbol{u}_{\boldsymbol{a}} = \boldsymbol{G}(\boldsymbol{X})[-\widehat{\boldsymbol{F}}(\boldsymbol{X}_{\boldsymbol{e}}|\widehat{\boldsymbol{W}}) - \widehat{\boldsymbol{\eta}}\boldsymbol{T}(\boldsymbol{s}) - \boldsymbol{K}\boldsymbol{E}(\boldsymbol{s})] \tag{15}$$

where$\boldsymbol{u}_{\boldsymbol{a}} = [u_{a1}, u_{a2}, u_{a3}, u_{a4}, u_x, u_y]^{\boldsymbol{T}}$, $\boldsymbol{G}(\boldsymbol{X}) = \text{diag}[1/g_z(\boldsymbol{X}), 1,1,1, 1/u_{a1}, 1/u_{a1}]$, $\widehat{\boldsymbol{F}}(\boldsymbol{X}) = [\hat{f}_z, \hat{f}_\phi, \hat{f}_\theta, \hat{f}_\psi, \hat{f}_x, \hat{f}_y]^{\boldsymbol{T}}$, $\boldsymbol{T}(\boldsymbol{s}) = [T_z(s_z), T_\phi(s_\phi), T_\theta(s_\theta), T_\psi(s_\psi), T_x(s_x), T_y(s_y)]^{\boldsymbol{T}}$, $\boldsymbol{E}(\boldsymbol{s}) = [E_z(s_z), E_\phi(s_\phi), E_\theta(s_\theta), E_\psi(s_\psi), E_x(s_x), E_y(s_y)]^{\boldsymbol{T}}$, $T_j(s_j) = (e^{4s_j} - 1)/(e^{4s_j} + 1)$, $E_j(s_j) = s_j/(e^{4s_j} + 1)$, $j = \phi, \theta, \psi, x, y, z$, $\widehat{\boldsymbol{\eta}} = \text{diag}[\hat{\eta}_z, \hat{\eta}_\phi, \hat{\eta}_\theta, \hat{\eta}_\psi, \hat{\eta}_x, \hat{\eta}_y]$ given by

$$\begin{cases} \hat{\eta} = \hat{\eta}_1 + \eta_2 \in \mathbb{R}^{6\times6} \\ \hat{\eta}_1 = \text{diag}[\hat{\eta}_{1,z}, \hat{\eta}_{1,\phi}, \hat{\eta}_{1,\theta}, \hat{\eta}_{1,\psi}, \hat{\eta}_{1,x}, \hat{\eta}_{1,y}] \in \mathbb{R}^{6\times6} \\ \dot{\hat{\eta}}_{1,k} = \Gamma_{\eta,k}^{-1}|\boldsymbol{s}_{\boldsymbol{k}}| \in \mathbb{R}^{6\times6}, j = z, \phi, \theta, \psi, x, y \\ \dot{\hat{\varepsilon}} = \boldsymbol{\Gamma}_{\boldsymbol{\varepsilon}}^{-1}\boldsymbol{s} \in \mathbb{R}^{6\times6} \\ \eta_2 = \text{diag}[\rho|\hat{\varepsilon}_z|, \rho|\hat{\varepsilon}_\phi|, \rho|\hat{\varepsilon}_\theta|, \rho|\hat{\varepsilon}_\psi|, \rho|\hat{\varepsilon}_x|, \rho|\hat{\varepsilon}_y|] \in \mathbb{R}^{6\times6} \end{cases} \tag{16}$$

with $\Gamma_{\eta,k} > 0$, $\boldsymbol{\Gamma}_{\boldsymbol{\varepsilon}} = \boldsymbol{\Gamma}_{\boldsymbol{\varepsilon}}^{\boldsymbol{T}} > 0 \in \mathbb{R}^{6\times6}$ and $\rho > 1$.

$\widehat{\boldsymbol{F}}(\boldsymbol{X})$is an approximation of the unknown system's dynamics, which is obtained using a RBFNN. A RBFNN is a feedforward 3-layer network thatuses the universal approximation theorem to approximate any smooth function on a compact set$\Omega \in \mathbb{R}^n$.RBFNNs have been used in many studies for their ability of accelerating learning speed and avoiding localminimum problem that make them suitable for real-time control systems with improved control accuracy,robustness and adaptability [13, 14, 15, 16]. The nonlinear function $\widehat{\boldsymbol{F}}(\boldsymbol{X})$is obtained using:

$$\widehat{\boldsymbol{F}}(\boldsymbol{X}) = \widehat{\boldsymbol{W}}^{\boldsymbol{T}}\boldsymbol{h}(\boldsymbol{X_e}) \tag{17}$$

Where$\boldsymbol{X_e} \in \mathbb{R}^{\boldsymbol{6}}$(with elements being $\boldsymbol{x_{e1}} = [e_j, \dot{e}_j]^T$)is the set of RBFNN's input,$\boldsymbol{h}(\boldsymbol{X_e}) = [h_z^T(x_{ez}), h_\phi^T(x_{e\phi}), h_\theta^T(x_{e\theta}), h_\psi^T(x_{e\psi}), h_x^T(x_{ex}), h_y^T(x_{ey})]^{\boldsymbol{T}} \in \mathbb{R}^{\boldsymbol{6m}}$ with $h_j(X_{ej}) = [h_{j1}, h_{j2}, \cdots, h_{jm}]^T$ being the radialbasis vector function where :

$$h_{ji}(X_{ej}) = \exp\left(-\frac{\|X_{ej}-\lambda_i\|^2}{2\beta_i^2}\right) \tag{18}$$

with $\lambda = [\lambda_1, \lambda_2, \cdots, \lambda_m]^T$ and $\beta = [\beta_1, \beta_2, \cdots, \beta_m]^T$being the centric vector and base width vector of theradial basis function, respectively, and $i = 1,2,\cdot\cdot\cdot, m$, $m$being the number of neurons in the hidden layer ofthe neural network(NN);and $\widehat{W} \in \mathbb{R}^{\boldsymbol{6m\times 6}}$is obtained from;

$$\dot{\widehat{\boldsymbol{W}}} = \boldsymbol{\Gamma}^{-\boldsymbol{1}}\boldsymbol{h}(\boldsymbol{x_e})\boldsymbol{s}^{\boldsymbol{T}} \tag{19}$$

with $\boldsymbol{\Gamma} = \boldsymbol{\Gamma}^{\boldsymbol{T}} > 0 \in \mathbb{R}^{6\times 6}$.

The difference between the RBFNN output $\widehat{\boldsymbol{F}}(\boldsymbol{X_e}|\widehat{\boldsymbol{W}})$and the exact nonlinear function $\boldsymbol{F}(\boldsymbol{X}) = [f_z, f_\phi, f_\theta, f_\psi, f_x, f_y]^{\boldsymbol{T}}$is expressed as:

$$\widehat{\boldsymbol{F}}(\boldsymbol{X_e}|\widehat{\boldsymbol{W}}) - \boldsymbol{F}(\boldsymbol{X}) = \widetilde{\boldsymbol{W}}^{\boldsymbol{T}}\boldsymbol{h}(\boldsymbol{X_e}) - \boldsymbol{\varepsilon}(\boldsymbol{X_e})\boldsymbol{I_6} \tag{20}$$

where $\boldsymbol{I_6} \in \mathbb{R}^6$is a unit column vector, $\widetilde{\boldsymbol{W}}$is the error ofweight matrix approximation and the RBFNN approximationerror vector is$\boldsymbol{\varepsilon}(\boldsymbol{X_e}) = [\varepsilon_z, \varepsilon_\phi, \varepsilon_\theta, \varepsilon_\psi, \varepsilon_x, \varepsilon_y]^{\boldsymbol{T}}$,which is assumed bounded by an unknown constant.

Theorem 1 *By considering the quadrotor model expressed by Eqs. 9-11 with unknown parameters, actuation faultsand external disturbances, by using the nonlinear control law expressed by Eq. (15), where the quantities expressedby Eqs. (16)-(19) are used, the quadrotor is stable and the control objective is achieved.*

Proof First, let us set the following equality:

$$\boldsymbol{M}\cdot\dot{\boldsymbol{X}}_{\boldsymbol{2}} = \boldsymbol{F}'(\boldsymbol{X}) + \boldsymbol{G}^{-\boldsymbol{1}}(\boldsymbol{X})\boldsymbol{u_a} + \boldsymbol{\xi}(\boldsymbol{X}, \boldsymbol{u_a}) \tag{21}$$

where $M = \mathrm{diag}[m_s, 1/b_1, 1/b_2, 1/b_3, m_s, m_s]$, $X_2 = [x_{12}, x_2, x_4, x_6, x_8, x_{10}]^T$, $\boldsymbol{\xi}(\boldsymbol{X}, \boldsymbol{u_a}) = [\xi_z, \xi_\phi, \xi_\theta, \xi_\psi, \xi_x, \xi_y]^T$and $\boldsymbol{F}'(\boldsymbol{X}) = [a_{11}x_{12} - g, a_1qr + a_2q\Omega_r + a_3p, a_4pr + a_5p\Omega_r + a_6q, a_7pq + a_8r, a_9x_8, a_{10}x_9]^T$.

The vector of filtered error functions, where Eqs.(15) and (20) are applied, can be expressed as follows:

$$\boldsymbol{M}\cdot\dot{\boldsymbol{s}} = \boldsymbol{M}\ddot{\boldsymbol{e}} + \boldsymbol{M}\cdot\boldsymbol{c}\cdot\dot{\boldsymbol{e}}$$
$$= -[\widetilde{\boldsymbol{W}}^{\boldsymbol{T}}\boldsymbol{h}(\boldsymbol{X_e}) - \boldsymbol{\varepsilon}(\boldsymbol{X_e})\boldsymbol{I_6}] + \boldsymbol{\xi}(\boldsymbol{X}, \boldsymbol{u_a}) - \widehat{\boldsymbol{\eta}}\boldsymbol{T}(\boldsymbol{s}) - \boldsymbol{KE}(\boldsymbol{s}) \tag{22}$$

where the tracking error vector $e = \boldsymbol{X_1} - \boldsymbol{X_{1d}} \in \mathbb{R}^6$(with$\dot{\boldsymbol{X}}_{\boldsymbol{1}} = \boldsymbol{X_2}, \boldsymbol{X_1} = [x_{11}, x_1, x_3, x_5, x_7, x_9]^T$)and $\boldsymbol{X_{1d}} \in \mathbb{R}^6$is thevector of desired values for $\boldsymbol{X_1}$) and the entries of the diagonal matrix $\boldsymbol{c}$are $c_j > 0$ (with $j = \phi, \theta, \psi, x, y, z$). Knowing that

$$\boldsymbol{F}(\boldsymbol{X}) = \boldsymbol{F}'(\boldsymbol{X}) + \boldsymbol{M}\cdot\boldsymbol{c}\cdot\dot{\boldsymbol{e}} - \boldsymbol{M}\ddot{\boldsymbol{X}}_{\boldsymbol{1d}} \tag{23}$$

Let us now consider the following candidate Lyapunov function:

$$V = V_1 + V_2 \tag{24}$$

with

$$V_1 = \frac{1}{2}\boldsymbol{s}^T\boldsymbol{M}\boldsymbol{s} + \frac{1}{2}\mathbf{tr}[\widetilde{\boldsymbol{W}}^T\boldsymbol{\Gamma}\widetilde{\boldsymbol{W}}] \quad (25)$$

where the error on $\widehat{\boldsymbol{W}}$is defined as follows:

$$\widetilde{\boldsymbol{W}} = \widehat{\boldsymbol{W}} - \boldsymbol{W}^* \quad (26)$$

$\boldsymbol{W}^* \in \mathbb{R}^{6m\times 6}$is the optimal weight matrix used hereonly for analytic purpose.Furthermore, by considering$\widehat{\boldsymbol{\eta}}_1\boldsymbol{I}_6$ as anestimationof the lumped disturbance $\xi(\boldsymbol{X},\boldsymbol{u_a})$ such that the approximation error is

$$\widetilde{\boldsymbol{\eta}}_1\boldsymbol{I}_6 = \widehat{\boldsymbol{\eta}}_1\boldsymbol{I}_6 - \boldsymbol{\xi}(\boldsymbol{X},\boldsymbol{u}_a) \quad (27)$$

we formulate

$$V_2 = \frac{1}{2}\mathbf{tr}[\widetilde{\boldsymbol{\eta}}_1^T\boldsymbol{\Gamma}_\eta\widetilde{\boldsymbol{\eta}}_1] + \frac{1}{2}\widetilde{\boldsymbol{\varepsilon}}^T\,\boldsymbol{\Gamma}_\varepsilon\widetilde{\boldsymbol{\varepsilon}} \quad (28)$$

where

$$\widetilde{\boldsymbol{\varepsilon}} = \widehat{\boldsymbol{\varepsilon}} - \boldsymbol{\varepsilon}(\boldsymbol{X}_e) \quad (29)$$

is a diagonal matrix of error on parameter $\widehat{\boldsymbol{\varepsilon}} \in \mathbb{R}^{6\times 6}$(the approximate RBFNN error).
The first derivative of$V_1$with respect to time inwhich Eq. (26) is applied is:

$$\dot{V}_1 = \boldsymbol{s}^T\boldsymbol{M}\dot{\boldsymbol{s}} + \mathrm{tr}\left[\widetilde{\boldsymbol{W}}^T\boldsymbol{\Gamma}\dot{\widetilde{\boldsymbol{W}}}\right]$$
$$= \boldsymbol{s}^T\boldsymbol{M}\dot{\boldsymbol{s}} + \mathrm{tr}\left[\widetilde{\boldsymbol{W}}^T\boldsymbol{\Gamma}\dot{\widehat{\boldsymbol{W}}}\right] \quad (30)$$

Using Eq. (22) and the update law given by (19) in Eq.(30) yields

$$\dot{V}_1 = \boldsymbol{s}^T\{-[\widetilde{\boldsymbol{W}}^T\boldsymbol{h}(\boldsymbol{X}_e) - \boldsymbol{\varepsilon}(\boldsymbol{X}_e)\boldsymbol{I}_6] + \boldsymbol{\xi}(\boldsymbol{X},\boldsymbol{u}_a) - \widehat{\boldsymbol{\eta}}\boldsymbol{T}(\boldsymbol{s}) - \boldsymbol{K}\boldsymbol{E}(\boldsymbol{s})\} + \mathbf{tr}\left[\widetilde{\boldsymbol{W}}^T\boldsymbol{\Gamma}\dot{\widehat{\boldsymbol{W}}}\right]$$
$$= \mathbf{tr}\left[\widetilde{\boldsymbol{W}}^T\left(\boldsymbol{\Gamma}\dot{\widehat{\boldsymbol{W}}} - \boldsymbol{h}(\boldsymbol{X}_e)\right)\boldsymbol{s}^T\right] + \boldsymbol{s}^T\boldsymbol{\varepsilon}(\boldsymbol{X}_e)\boldsymbol{I}_6 + \boldsymbol{s}^T\,\boldsymbol{\xi}(\boldsymbol{X},\boldsymbol{u}_a) - \boldsymbol{s}^T\widehat{\boldsymbol{\eta}}\boldsymbol{T}(\boldsymbol{s}) - \boldsymbol{s}^T\boldsymbol{K}\boldsymbol{E}(\boldsymbol{s}) \quad (31)$$

The first derivative of Eq. (28) with respect to time,in which the identities given by Eqs. (27) and (29) are applied, is obtained as follows:

$$\dot{V}_2 = \mathbf{tr}[\widetilde{\boldsymbol{\eta}}_1^T\boldsymbol{\Gamma}_\eta\dot{\widetilde{\boldsymbol{\eta}}}_1] + \widetilde{\boldsymbol{\varepsilon}}^T\boldsymbol{\Gamma}_\varepsilon\dot{\widetilde{\boldsymbol{\varepsilon}}} = \mathbf{tr}[\widetilde{\boldsymbol{\eta}}_1^T\boldsymbol{\Gamma}_\eta\dot{\widehat{\boldsymbol{\eta}}}_1] + \widetilde{\boldsymbol{\varepsilon}}^T\boldsymbol{\Gamma}_\varepsilon\dot{\widehat{\boldsymbol{\varepsilon}}} \quad (32)$$

Therefore, using Eqs. (31) and (32), by applying Eq.(29) and the update rule for parameter $\hat{\varepsilon}$given by Eq.(16), the first-time derivative of the Lyapunov's functionis obtained as follows:

$$\dot{V} = \mathbf{tr}\left[\widetilde{\boldsymbol{W}}^T\left(\boldsymbol{\Gamma}\dot{\widehat{\boldsymbol{W}}} - \boldsymbol{h}(\boldsymbol{X}_e)\right)\boldsymbol{s}^T\right] + \boldsymbol{s}^T\boldsymbol{\varepsilon}(\boldsymbol{X}_e)\boldsymbol{I}_6 + \boldsymbol{s}^T\,\boldsymbol{\xi}(\boldsymbol{X},\boldsymbol{u}_a) - \boldsymbol{s}^T\widehat{\boldsymbol{\eta}}\boldsymbol{T}(\boldsymbol{s}) - \boldsymbol{s}^T\boldsymbol{K}\boldsymbol{E}(\boldsymbol{s}) + \mathbf{tr}[\widetilde{\boldsymbol{\eta}}_1^T\boldsymbol{\Gamma}_\eta\dot{\widehat{\boldsymbol{\eta}}}_1] + \widetilde{\boldsymbol{\varepsilon}}^T\boldsymbol{\Gamma}_\varepsilon\dot{\widehat{\boldsymbol{\varepsilon}}}$$
$$= \boldsymbol{s}^T(\widehat{\boldsymbol{\varepsilon}} - \widetilde{\boldsymbol{\varepsilon}})\boldsymbol{I}_6 + \boldsymbol{s}^T\boldsymbol{\xi}(\boldsymbol{X},\boldsymbol{u}_a) - \boldsymbol{s}^T\widehat{\boldsymbol{\eta}}\boldsymbol{T}(\boldsymbol{s}) - \boldsymbol{s}^T\boldsymbol{K}\boldsymbol{E}(\boldsymbol{s}) + \mathbf{tr}[\widetilde{\boldsymbol{\eta}}_1^T\boldsymbol{\Gamma}_\eta\dot{\widehat{\boldsymbol{\eta}}}_1] + \widetilde{\boldsymbol{\varepsilon}}^T\boldsymbol{\Gamma}_\varepsilon\dot{\widehat{\boldsymbol{\varepsilon}}} \quad (33)$$
$$= \boldsymbol{s}^T\boldsymbol{\xi}(\boldsymbol{X},\boldsymbol{u}_a) - \boldsymbol{s}^T\widehat{\boldsymbol{\eta}}\boldsymbol{T}(\boldsymbol{s}) - \boldsymbol{s}^T\boldsymbol{K}\boldsymbol{E}(\boldsymbol{s}) + \mathbf{tr}[\widetilde{\boldsymbol{\eta}}_1^T\boldsymbol{\Gamma}_\eta\dot{\widehat{\boldsymbol{\eta}}}_1] + \boldsymbol{s}^T\widehat{\boldsymbol{\varepsilon}}\boldsymbol{I}_6$$

Considering that in case of a severe perturbation causedby the lumped disturbance $\xi(\boldsymbol{X},\boldsymbol{u_a})$ the variable $\mathbf{s}$ diverges fromthe origin such that $T_i(s_i) \cong 1$, Eq. (33)can be rewritten as follows:

$$\dot{V} \cong \boldsymbol{s}^T\boldsymbol{\xi}(\boldsymbol{X},\boldsymbol{u}_a) - \boldsymbol{s}^T\widehat{\boldsymbol{\eta}}\boldsymbol{I}_6 - \boldsymbol{s}^T\boldsymbol{K}\boldsymbol{E}(\boldsymbol{s}) + \mathbf{tr}[\widetilde{\boldsymbol{\eta}}_1^T\boldsymbol{\Gamma}_\eta\dot{\widehat{\boldsymbol{\eta}}}_1] + \boldsymbol{s}^T\widehat{\boldsymbol{\varepsilon}}\boldsymbol{I}_6$$
$$= \boldsymbol{s}^T(\widehat{\boldsymbol{\eta}}_1 - \widetilde{\boldsymbol{\eta}}_1)\boldsymbol{I}_6 - \boldsymbol{s}^T(\widehat{\boldsymbol{\eta}}_1 + \boldsymbol{\eta}_2)\boldsymbol{I}_6 - \sum_{i=1}^{6} K_i\frac{s_i^2}{\exp(s_i)+1} + \mathbf{tr}[\widetilde{\boldsymbol{\eta}}_1^T\boldsymbol{\Gamma}_\eta\dot{\widehat{\boldsymbol{\eta}}}_1] + \boldsymbol{s}^T\widehat{\boldsymbol{\varepsilon}}\boldsymbol{I}_6 \quad (34)$$
$$= \boldsymbol{s}^T\widetilde{\boldsymbol{\eta}}_1\boldsymbol{I}_6 - \boldsymbol{s}^T\boldsymbol{\eta}_2\boldsymbol{I}_6 - \sum_{i=1}^{6} K_i\frac{s_i^2}{\exp(s_i)+1} + \mathbf{tr}[\widetilde{\boldsymbol{\eta}}_1^T\boldsymbol{\Gamma}_\eta\dot{\widehat{\boldsymbol{\eta}}}_1] + \boldsymbol{s}^T\widehat{\boldsymbol{\varepsilon}}\boldsymbol{I}_6$$

where $\hat{\eta}$and $\xi(\boldsymbol{X};\ \boldsymbol{u_a})$ are replaced by their expressionsgiven by Eqs. (16) and (27).

Let us apply in Eq. (34) the update rule$\dot{\hat{\eta}}_{1,k}$(with$k = z, \phi, \theta, \psi, x, y = 1,2,3,4,5,6$) given by Eq. (16) toobtain:

$$\dot{V} = \mathbf{tr}\left[\tilde{\boldsymbol{\eta}}_1^T\left(\boldsymbol{\Gamma}_\eta \dot{\hat{\boldsymbol{\eta}}}_1 - \boldsymbol{I}_6 \boldsymbol{s}^T\right)\right] - \sum_{i=1}^{6} K_i \frac{s_i^2}{\exp(s_i)+1} + \boldsymbol{s}^T \hat{\boldsymbol{\varepsilon}} \boldsymbol{I}_6 - \boldsymbol{s}^T \boldsymbol{\eta}_2 \boldsymbol{I}_6$$

$$= \sum_{k=1}^{6}\left[\tilde{\eta}_{1,k}\left(\Gamma_{\eta,k}\dot{\hat{\eta}}_{1,k} - s_k\right)\right] - \sum_{i=1}^{6} K_i \frac{s_i^2}{\exp(s_i)+1} + \boldsymbol{s}^T \hat{\boldsymbol{\varepsilon}} \boldsymbol{I}_6 - \boldsymbol{s}^T \boldsymbol{\eta}_2 \boldsymbol{I}_6 \tag{35}$$

$$\leq \sum_{k=1}^{6}\left[\left|\tilde{\eta}_{1,k}\right|\left(\Gamma_{\eta,k}\dot{\hat{\eta}}_{1,k} - |s_k|\right)\right] - \sum_{i=1}^{6} K_i \frac{s_i^2}{\exp(s_i)+1} + \boldsymbol{s}^T \hat{\boldsymbol{\varepsilon}} \boldsymbol{I}_6 - \boldsymbol{s}^T \boldsymbol{\eta}_2 \boldsymbol{I}_6$$

$$= -\sum_{i=1}^{6} K_i \frac{s_i^2}{\exp(s_i)+1} + \boldsymbol{s}^T(\hat{\boldsymbol{\varepsilon}} - \boldsymbol{\eta}_2)\boldsymbol{I}_6 \leq = -\sum_{i=1}^{6} K_i \frac{s_i^2}{\exp(s_i)+1} + \|\boldsymbol{s}\|(\|\hat{\boldsymbol{\varepsilon}}\| - \|\boldsymbol{\eta}_2\|)$$

By using the value $\boldsymbol{\eta}_2$expressed by Eq. (16) weobtain

$$\dot{V} \leq -\sum_{i=1}^{6} K_i \frac{s_i^2}{\exp(s_i)+1} + \|\boldsymbol{s}\|\left(\frac{1}{\rho} - 1\right)\|\boldsymbol{\eta}_2\|$$

With $K_i > 0$ and $\rho > 1$, we have$\dot{V} \leq 0$. Therefore, theclosed-loop system is asymptotically stable despite uncertaindynamics, external disturbances and actuationfaults. Hence, we conclude that the control objective isachieved when theproposed control law is used with thedefined constant and dynamic parameters, as accordingto the Barbalat's lemma $\boldsymbol{e} \to \mathbf{0}$when$t \to \infty$.

V. SIMULATION RESULTS AND DISCUSSION

To illustrate the efficiency of the proposed quadrotoradaptive nonlinear FTC (QANFTC), here we presentsimulationresults obtained using MATLAB/ SIMULINK.For benchmarking purpose, these results are comparedto those obtained using the robust SOSMC developedin [1] for the quadrotor, which is implemented usingknown system parameters.

Parameters of the simulated UAV are given in table1 [1, 13]. It is assumed that $\boldsymbol{m}_s$represents the totalweight of the UAV, which includes 1.1$\boldsymbol{kg}$for the UAVand 0.77$\boldsymbol{kg}$for the payload.The selected values for the controller's design parameters and for the RBFNN are given in table 2.For this simulation,initial values for positions andthe Euler's angles are considered to be zero. The controlobjective is to track the referencepositions and anglesgiven in table 3.

Table 1: Parameters of the simulated quadrotor

Variable	Values	Units
m_s	1.87	kg
l	0.21	m
$I_x = I_y$	1.22	Ns^2/rad
I_z	2.2	Ns^2/rad
J_r	0.2	Ns^2/rad
$k_i(i = 1,2,3)$	0.1	Ns/m
$k_i(i = 4,5,6)$	0.12	Ns/m
g	9.81	m/s^2
b	5	Ns^2
k	2	Nm/s^2
C	1	−

Table 2: QANFTC and RBFNN parameters

Parameters	Values
$K_j(j = \phi, \theta, \psi, x, y, z)$	5
$c_j(j = \phi, \theta, \psi, x, y, z)$	5
$\rho_j(j = \phi, \theta, \psi, x, y, z)$	2.5
$\gamma_j(j = \phi, \theta, \psi, x, y, z)$	0.35
$\gamma_{\eta_j}(j = \phi, \theta, \psi, x, y, z)$	0.035
$\gamma_{\varepsilon_j}(j = \phi, \theta, \psi, x, y, z)$	0.035
$\lambda_i(i = 1,2,3,4,5)$	0.1
$\beta_i(i = 1,2,3,4,5)$	0.5

Table 3: Desired positions and angles

Variables	Values	Time (in sec)
$[x_d, y_d, z_d]$	$[6.0, 6.0, 6.0]m$	$0 \leq t < 10$
	$[3.0, 6.0, 6.0]m$	$10 \leq t < 20$
	$[3.0, 3.0, 6.0]m$	$20 \leq t < 30$
	$[6.0, 3.0, 6.0]m$	$30 \leq t < 40$
	$[6.0, 6.0, 6.0]m$	$40 \leq t < 50$
	$[6.0, 6.0, 0.0]m$	$t \geq 50$
$[\phi_d, \theta_d, \psi_d]$	$[0.0, 0.0, 0.5]$rad	$0 \leq t < 50$
	$[0.0, 0.0, 0.0]$rad	$t \geq 50$

Table 4: Aerodynamics forces and torques

Disturbances	Values	Time (in sec)
$[d_x, d_y, d_z]$	$[0.0, 0.0, 0.0]N$	$0 \leq t < 15$
	$[0.0, 1.0, 1.0]N$	$15 \leq t < 20$
	$[1.0, 0.0, 1.0]N$	$20 \leq t < 50$
	$[1.0, 1.0, 1.0]N$	$t \geq 50$
$[d_\phi, d_\theta, d_\psi]$	$[0.0, 0.0, 0.0]Nm$	$0 \leq t < 50$
	$[1.0, 1.0, 1.0]Nm$	$t \geq 50$

To check robustness in case of external disturbances,we apply to the system, on the six degrees of freedom, disturbancesthat are the aerodynamics forces andtorques given in table 4. Simulation results show that despite external disturbances on the six degrees of freedom the UAV tracks the desired trajectory with accuracy.

To check robustness in case of parameter changes,we consider that the UAV drops its load at $t = 40s$ such that $\boldsymbol{m}_s$varies from 1.87kg to 1.1kg.

To check robustness against actuation faults, weconsider a scenario in which, at $t = 25s$, the first andthird motors losesimultaneously 25% and 30% of theircontrol effectiveness, respectively. In this scenario, it isalso assumed that a 40% loss of effectiveness occurs inthe second and the fourth motor at $t = 50s$. Simulation results depicted by Figs. 1, 2 and 3show clearlythat, with the designed controller, the UAV is able tostay perfectly in balance during flight when the loadattached to it is dropped, when external disturbancesand actuation faults occur for many motors. As illustrated by Fig. 1, a good tracking accuracy is obtainedwith the proposed QANFTC while the robust controllerfrom [1] fails and leads to a crash at $t = 25sec$ due toactuator faults.

Figure 3 illustratesthe UAV's trajectory in $3D$ when the two controllersare used. One can see clearly that despite multipleperturbations, the UAV remains in normal flight with theproposed controller (see Fig. 3 (a)), while it loses itsbalanceand crashes with the SOSMC (see Fig. 3 (b)).

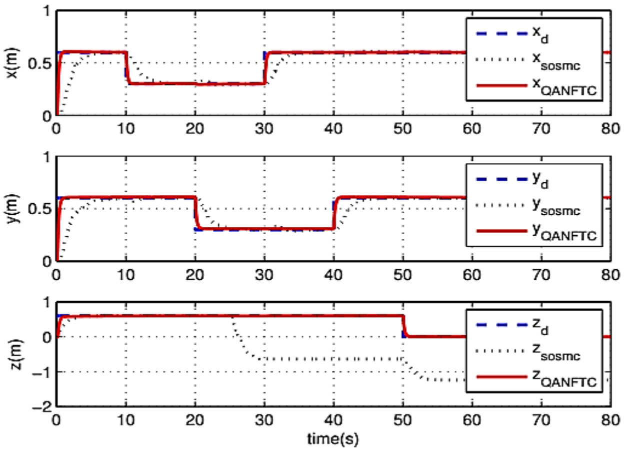

Fig. 1: x, y and z positions with the proposed QANFTC and with the robust SOSMC from [1] (with multiple perturbations).

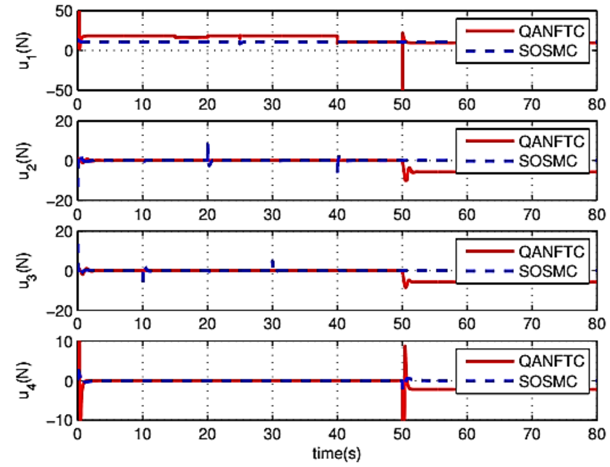

Fig. 2: Control signals u_1, u_2, u_3 and u_4 with the proposed QANFTC and with the robust SOSMC from [1](with multiple perturbations).

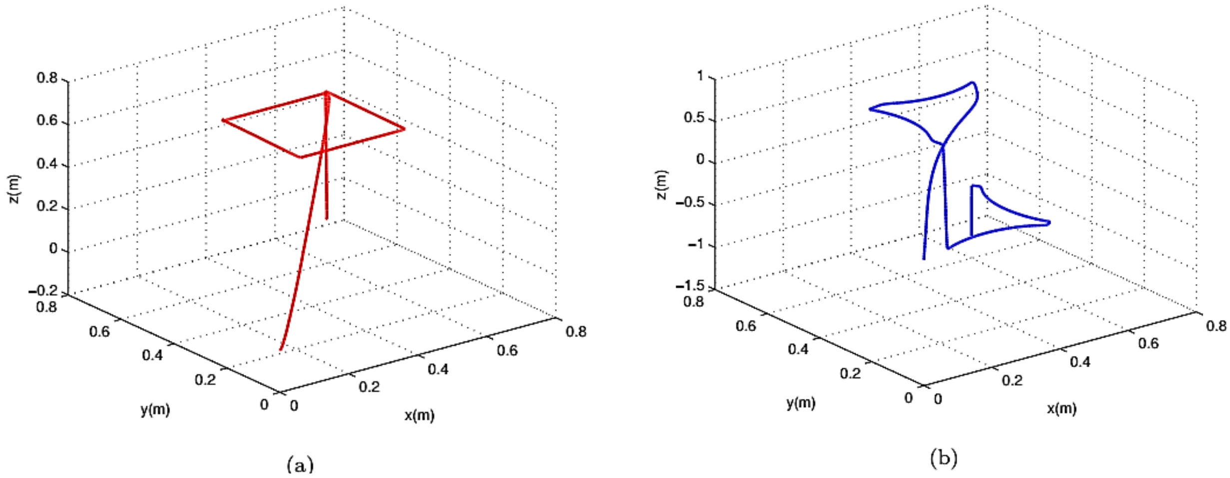

Fig. 3: 3D trajectory (a) with the proposed QANFTC(with multiple perturbations) and (b) with the robustSOSMC from [1]

VI. CONCLUSION

In this paper, an adaptive nonlinear controller has been designed for a six degree of freedom quadrotor unmanned aerial vehicle such that issues related to uncertain or varying parameters, external disturbances and multiple actuation failures can be tackled. Radial basis function neural networks have been used to provide approximation of uncertain dynamics and their update rule have been designed. To cancel the effects of external disturbances combined with those of actuation
faults, some dynamic parameters have been incorporated in the control law. Suitable update rules for these time varying parameters have been designed. Knowing that neural network approximation errors can alsoaffect the control system performance, a dynamic parameter has been used for compensating the effects ofthese errors. Through Al yapunov stability analysis, ithas been proved that the proposed control law withits dynamic parameters guarantee the closed-loop system stability while assuring that the control objectiveis achieved. Results obtained with the proposed controller, under no perturbation condition, have been compared to those obtained with a robust second order sliding mode controller. It has been illustrated how under the aforementioned condition the proposed controller outperformed its counterpart. In order to illustrate the effectiveness of the proposed controller in severe operation conditions such as simultaneous multiple motorfaults, aerodynamics forces and torques, simulation results have been presented. It has been shown that the proposed controller ensures very good tracking accuracy and a fast response despite simultaneous severe perturbations.
A future research could extend the proposed quadrotor's controller by integrating a state observer so that the use of some sensors could be avoided. Experimental validation of theoretical results presented in this paper could be performed as well.

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