Adaptive Control with Neural Networks-based Disturbance Observer for a Spherical UAV

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Abstract: This paper develops a control scheme for a Spherical Unmanned Aerial Vehicle (UAV) which can be used in complex scenarios where traditional navigation and communications systems would not succeed. The proposed scheme is based on the nonlinear control theory combined with Adaptive Neural-Networks Disturbance Observer (NN-DOB) and controls the attitude and altitude of the UAV in presence of model uncertainties and external disturbances. The NN-DOB can effectively estimate the uncertainties without the knowledge of their bounds and the control system stability is proven using Lyapunov’s stability theorems. Numerical simulation results demonstrate the validity of the proposed method on the UAV under model uncertainties and external disturbances.

Keywords: Spherical UAV, model uncertainties and external disturbances, disturbance observer, adaptive control, neural networks.

1. INTRODUCTION

Recent researches (Gui et al. [2015], Mizutani et al. [2015]) have proposed the design of ‘spherical-like’ UAVs. In this article the focus is about a coaxial, flap actuated, spherical helicopter, developed in Cranfield University with the specific purpose of exploration and exploitation of complex environments (Dixon and Fernandez [2013]).

The spherical frame provides protection to the inner components of the UAV and allows to roll along the floor if the environment permits. The coaxial motors provide as much thrust as possible in the small volume of the sphere and allow yaw control through differential propeller speed. The flaps, placed below the propellers, allow a decoupled roll and pitch control in a thrust vectoring manner. The final result of this design is a well-protected, compact, easily controlled, flexible and agile UAV for operations in complex environments.

As in the spherical UAV, system identification is quite challenging in small and unconventional airframes. Modelled dynamics of such an airframe often contain uncertainties. Moreover, small external disturbances could become severe since they might be relatively strong to such a platform, unlike to relatively large and conventional aircraft. Therefore, when designing a flight control system for small and/or unconventional UAVs, incorporating uncertainties and disturbances is of great importance.

This paper aims to develop a control system for the spherical UAV, which is able to cope with model uncertainties and external disturbances. In order to achieve this aim, we propose an adaptive control system with Neural Network-Disturbance Observer. The proposed approach adjusts rotor speed and flap angles to control attitude and altitude of the spherical UAV.

The basic control system is designed based on the Lyapunov control theory. NN-DOB adaptively estimates model uncertainties and external disturbances and these estimates are incorporated in the original control commands obtained from the Lyapunov control theory. The stability of the entire system is analytically investigated. The analysis results confirm that the proposed control system guarantees the stability of entire system under the presence of uncertainties and disturbances, even without knowledge of their bounds.

The main advantage of the proposed control method is the applicability to every rigid (DoF) body in which forces and torques can be applied.

This paper is organised as follows: Section 2 introduces the notations used throughout this paper and describes the dynamic model of the spherical UAV. Sections 3 explains the proposed control method for a single integrator system and its most useful extensions. Section 4 describes the application of the proposed control method on the spherical UAV. Control performance of the proposed method is demonstrated via numerical simulations in Section 5 and, finally, Section 6 presents the conclusions.

2. MODELING

The final design of the spherical UAV is shown in Fig. 1; the body-fixed frame $\{x_b, y_b, z_b\}$, is located in the Body Axis Centre (BAC), which is the geometric centre of...
The frame flaps make the UAV behave as a thrust vectored nozzle; as the applied torques in the body frame \( B \) \( \alpha \)-configuration.

second, the Earth is flat and two assumptions: first, the body is assumed to be rigid; second, the Earth is flat and \( E \) is considered inertial. The frame \( E \) is selected with the North-East-Down (NED) configuration.

2.1 Actuation principles

The actuation system is composed of two contra-rotating motors along \( z \)-axis and provides a force \( F \) and a torque \( \tau \); the relation with the PWMs is found with a test rig.

\[
F = f_1(PWM_1, PWM_2) \frac{1}{1 + \tau_m s} \tag{1}
\]

\[
\tau = f_2(PWM_1, PWM_2) \frac{1}{1 + \tau_m s} \tag{2}
\]

where \( \tau_m \) represents a first order time constant and \( f_1 \) and \( f_2 \) are nonlinear function of both PWM1 and PWM2.

Define \( [X Y Z]_{Act}^T \) as the applied forces and \( [L M N]_{Act}^T \) as the applied torques in the body frame \( B \). The two flaps make the UAV behave as a thrust vectored nozzle; the force \( F \) produced by the motors is steered in three dimensions due to the flap angles \( \alpha_1 \) and \( \alpha_2 \):

\[
\begin{bmatrix}
X \\
Y \\
Z
\end{bmatrix}_{Act} = \begin{bmatrix}
F_x \\
F_y \\
F_z
\end{bmatrix} = \frac{1}{\sqrt{c_{\alpha_1}^2 s_{\alpha_2}^2 + c_{\alpha_2}^2 s_{\alpha_1}^2}} \begin{bmatrix}
-c_{\alpha_1} s_{\alpha_2} \\
s_{\alpha_1} c_{\alpha_2}
\end{bmatrix} F
\] \tag{3}

From now on we define \( c_x = \cos x, s_x = \sin x \) and \( f_x = \tan x \) for the simplicity of the notation. \( L, M \) and \( N \) torques are generated because the forces \( X \) and \( Y \) are applied in a point on the \( z \)-axis, \( dV \) below the BAC.

\[
\begin{bmatrix}
L \\
M \\
N
\end{bmatrix}_{Act} = \begin{bmatrix}
0 & F_y & 0 \\
0 & F_z & 0 \\
dV & F_x & 0
\end{bmatrix} = \begin{bmatrix}
-dF_y \\
-dF_z \\
dV F_x
\end{bmatrix} \tag{4}
\]

Merging (3) and (4), the actuators action is shown in (5):

\[
\begin{bmatrix}
X \\
Y \\
Z \\
L \\
M \\
N
\end{bmatrix}_{Act} = \begin{bmatrix}
F_x \\
F_y \\
F_z \\
-dF_y \\
dV F_x \\
-dV F_y + dV F_z
\end{bmatrix} \frac{1}{\tau_m s + 1} \tag{5}
\]

2.2 Dynamics

Consider the motion of the body-fixed frame \( B \) about an Earth-fixed reference frame \( E = \{x_e, y_e, z_e\} \). There are two assumptions: first, the body is assumed to be rigid; second, the Earth is flat and \( E \) is considered inertial. The frame \( E \) is selected with the North-East-Down (NED) configuration.

From the Newton-Euler equations, it holds:

\[
\begin{bmatrix}
X \\
Y \\
Z \\
L \\
M \\
N
\end{bmatrix} = \begin{bmatrix}
m \dot{u} + m \begin{bmatrix}
p \\
q \\
r
\end{bmatrix} \times \begin{bmatrix}
u \\
v \\
w
\end{bmatrix} \\
I_B \ddot{p} + I_B \begin{bmatrix}
p \\
q \\
r
\end{bmatrix} \times \begin{bmatrix}
p \\
q \\
r
\end{bmatrix}
\end{bmatrix} \tag{6}
\]

\[
\begin{bmatrix}
L \\
M \\
N
\end{bmatrix} = I_B \begin{bmatrix}
\ddot{p} \\
\ddot{q} \\
\ddot{r}
\end{bmatrix} + \begin{bmatrix}
p \\
q \\
r
\end{bmatrix} \begin{bmatrix}
p \\
q \\
r
\end{bmatrix} \tag{7}
\]

where \( m \) is the UAV mass, \( I_B \) is the Inertia matrix in the body frame \( B \), \( v_B = [u v w]^T \) is the linear velocity in \( B \), \( \omega = [p q r]^T \) is the angular velocity in \( B \), \( F = [X Y Z]^T \) are the applied forces in \( B \) and \( T = [L M N]^T \) are the applied torques in \( B \). \( F \) and \( T \) include gravity contribution and external disturbances.

The relation between the body-fixed angular velocity \( \omega \) and the Euler angles derivatives, \( \dot{\eta} = [\dot{\phi} \dot{\theta} \dot{\psi}]^T \), is determined writing the body rates components into the inertial frame:

\[
\dot{\eta} = \begin{bmatrix}
1 & s_{\alpha_1} t_{\alpha_2} & c_{\alpha_2} \\
0 & c_{\alpha_1} & s_{\alpha_1} c_{\alpha_2} \\
0 & -c_{\alpha_1} & s_{\alpha_1} c_{\alpha_2}
\end{bmatrix} \omega = J \omega \tag{8}
\]

Therefore, using the Direct Cosine Matrix (DCM), the linear velocities in the reference frame are computed as:

\[
v_E = \frac{d}{dt} \begin{bmatrix}
P_x \\
P_y \\
P_z
\end{bmatrix} = DCM^T v_B \tag{9}
\]

The integration of (8) and (9) with the proper initial condition makes the position and attitude of the UAV known. For more details, see Stevens et al. [2015].

3. ADAPTIVE CONTROL LAW DESIGN

The proposed control system considers the system dynamics as a single integrator system:

\[
\dot{x} = k \cdot u + D(x, u, t) \tag{10}
\]

where \( x \) is the state to be controlled, \( k \) is a known constant and \( D(x, u, t) \) denotes a disturbance. Note that model uncertainties, external disturbances and/or neglected dynamics are incorporated in the disturbance, \( D(x, u, t) \). The aim of the control law is to make \( x \) follow a desired command \( x_C \). Define the tracking error as

\[
e = x_C - x \tag{11}
\]

Define a positive definite Lyapunov function

\[
V_1 = \frac{1}{2} e^2 \tag{12}
\]

The derivative of \( V_1 \) is

\[
\dot{V}_1 = \dot{e} e = e (\dot{x}_C - \dot{x}) = e (\dot{x}_C - k \cdot u - D(x, u, t)) \tag{13}
\]

This mean that, if we could choose

\[
u^* = \frac{1}{k} (\dot{x}_C - D(x, u, t) + \alpha e), \quad \alpha > 0 \tag{14}
\]

We could obtain

\[
\dot{V}_1^* = -\alpha e^2 \tag{15}
\]

Which is negative definite. In practice, the uncertainty \( D(x, u, t) \) is (obviously) unknown, and it is also difficult to know an upper bound \( D \) that achieves

\[
||D(x, u, t)|| < D \forall x, u, t
\]

For that reason an online adaptive observer is proposed for the estimation of \( D \). The proposed control law achieves the
tracking of the command $x_C$ along with the estimation of the uncertainty.

3.1 Disturbance Estimation

The NN-DOB is implemented with a Radial Basis Function Neural Network (RBF-NN), which has an efficient capability for approximating nonlinear dynamics; see Lavrentsky and Wise [2012] for more details. The NN-DOB estimator has an input layer, a hidden layer and an output layer, as shown in Fig. 2.

Fig. 2. RBF-NN structure.

The hidden layer is composed of $N$ neurons, each one with a centre, $\mu_i$, and a width, $\sigma_i$. Each hidden node contains a RBF, a nonlinear function satisfying $\phi(x) = \phi(||x||)$. The output depends only on the distance from the center, scaled by the width:

$$\phi_i(e) = f(||e - \mu_i||/\sigma_i)$$  \hspace{1cm} \hspace{1cm} (16)

The most used RBF are gaussian, logarithmic and multi-quadric functions. The output layer is computed using the following weighted sum:

$$D_\phi = \sum_{i=1}^{N} W_i \phi_i(e) = W^T \Phi$$  \hspace{1cm} \hspace{1cm} (17)

where $W_i$ is the weight of the $i$th hidden neuron and the output, $W = [W_1 \cdots W_N]^T$ and $\Phi = [\phi_1 \cdots \phi_N]^T$. Define $\delta$ as the minimum estimation error between the real disturbance and $D_\phi$ and $W^*$ as the weight vector that achieves the minimum $\delta$:

$$W^* = \arg \min_W (||D - D_\phi||)$$  \hspace{1cm} \hspace{1cm} (18)

So that

$$D(x, u, t) = D_\phi(W^*) + \delta = W^T \Phi + \delta$$  \hspace{1cm} \hspace{1cm} (19)

The estimation error $\delta$ and the optimal weight $W^*$ are unknown, so the total disturbance $D$ is estimated as

$$\hat{D} = W^T \Phi(e) + \hat{\delta}$$  \hspace{1cm} \hspace{1cm} (20)

Where $\hat{W}$ and $\hat{\delta}$ are calculated through an adaptive law.

3.2 Control Law

Define the Lyapunov function

$$V_2 = V_1 + \frac{1}{2\eta_1} (W^* - W)^T (W^* - W) + \frac{1}{2\eta_2} (\delta - \hat{\delta})^2$$  \hspace{1cm} \hspace{1cm} (21)

This function $V_2$ can be rewritten as $V_2 = \frac{1}{2} z^T P z$, where

$$z = \begin{bmatrix} W^* - W \\ \delta - \hat{\delta} \end{bmatrix}, \quad P = \text{diag} \left\{ 1, \frac{1}{\eta_1} I_{N \times N}, \frac{1}{\eta_2} \right\}$$  \hspace{1cm} \hspace{1cm} (22)

Note that $V_2$ is positive definite with respect to the variable $z$, and not only w.r.t the error $e$. The derivative of $V_2$ is

$$\dot{V}_2 = c e + \frac{1}{\eta_1} (W^* - W)^T (\dot{W}^* - \dot{W}) + \frac{1}{\eta_2} (\delta - \hat{\delta})(\dot{\delta} - \hat{\delta})$$  \hspace{1cm} \hspace{1cm} (23)

For every disturbance the couple $(W^*, \delta)$ is fixed, so we can assume

$$\dot{W}^* = 0$$  \hspace{1cm} \hspace{1cm} (24)

$$\dot{\delta} = 0$$  \hspace{1cm} \hspace{1cm} (25)

Substituting (13), (24) and (25) into (23) yields

$$\dot{V}_2 = e (\dot{x}_C - k u - D) - \frac{1}{\eta_1} (W^* - W)^T \dot{W} - \frac{1}{\eta_2} (\delta - \hat{\delta}) \dot{\delta}$$  \hspace{1cm} \hspace{1cm} (26)

Design the adaptive law as

$$\dot{\hat{W}} = -\eta_1 \Phi e$$  \hspace{1cm} \hspace{1cm} (27)

$$\dot{\hat{\delta}} = -\eta_2 e$$  \hspace{1cm} \hspace{1cm} (28)

Design the control action as

$$u = \frac{1}{k} (\alpha e + \dot{x}_C - \hat{D})$$  \hspace{1cm} \hspace{1cm} (29)

where $\hat{D}$ is calculated from (20) and $\alpha, \eta_1, \eta_2$ are positive tuning parameters. Substituting (27), (28) and (29) into (26) yields

$$V_2 = e (-\alpha e + \hat{D} - D) + (W^* - W)^T \Phi e + (\delta - \hat{\delta}) e = -\alpha e^2$$  \hspace{1cm} \hspace{1cm} (30)

This control action makes the derivative of $V_2$ only negative semi definite, and for that reason the stability is checked with the Barbalat’s Lemma. Define $\hat{V}_2$ as:

$$\hat{V}_2 = -2\alpha^2 e^2 - 2\alpha e (-\alpha e + D - D)$$  \hspace{1cm} \hspace{1cm} (31)

Since $e, u, D, \hat{D}$ are all bounded, then $\hat{V}_2$ is bounded, hence $V_2$ is uniformly continuous. Combined with the fact that $V_2$ is bounded from below and $\hat{V}_2$ is negative semi-definite, then it infers that $\hat{V}_2 \to 0$ as $t \to \infty$.

3.3 Estimation Direction

The disturbance equation (19) can be rewritten as

$$D = W^T \Phi(e) + \delta = [\Phi^T 1] [W^* \delta] = p^T L^*$$  \hspace{1cm} \hspace{1cm} (32)

Where $L^* = [W^* \delta]$ and $p^T = [\Phi^T 1]$ is the linear map between $L^*$ and $D$. Note that $p^T \in \mathbb{R}^{1 \times (N+1)}$, so its kernel has rank

$$\text{rank} (\ker(p^T)) = N$$  \hspace{1cm} \hspace{1cm} (33)

All $L$ which get the correct disturbance estimation are in $\mathcal{L}$:

$$\mathcal{L} = \{ L | L = L^* + L_{ker}, \ L_{ker} = \text{span} (\ker(p^T)) \}$$  \hspace{1cm} \hspace{1cm} (34)

The estimation is perfect if $L$ reaches the set $\mathcal{L}$. The adaptive law (27) and (28) can be written as

$$\dot{L} = -\frac{\eta_1}{\eta_2} \Phi e, \ L(0) = L_0$$  \hspace{1cm} \hspace{1cm} (35)

Note that if $\eta_1 = \eta_2 = \eta$, the estimation action is

$$\dot{L} = -\eta \Phi e, \ L(0) = L_0$$  \hspace{1cm} \hspace{1cm} (36)

From the basic algebra theorem,

$$\text{Im}(p) \perp \ker(p^T)$$  \hspace{1cm} \hspace{1cm} (37)

The estimation update is perpendicular to $\mathcal{L}$, so it is made in the fastest direction and the set of weights reachable from $L_0$ is $L_{\text{nearest}}$, as shown in Fig. 3.
where $M$ is the mass of the vehicle. From (6), the relation between equations (6), (7) because the inputs are directly inte-
resolving the control allocation problem linearizing (5).

This characteristic generalizes the control structure, as it can be applied to any system that acts as a single integrator.

3.5 Non-Linear MIMO Extension

The control laws (27), (28) and (29) can be extended to every Non-Linear, Multi Input Multi Output affine-in-the-
control (NL-MIMO-AC) system whose input-to-state map $g(x)$ has rank bigger than the state dimension. Consider
the following dynamic system:

$$\dot{x} = f(x) + g(x)u + D$$

$$x \in \mathbb{R}^N, D \in \mathbb{R}^N, u \in \mathbb{R}^M$$

where $M \geq N$; if the map $g(x) : \mathbb{R}^M \rightarrow \mathbb{R}^N$ has always rank $\geq N$ there exist an inverse function for every state $x$.

$$\text{rank } g(x) \geq N \Rightarrow \forall x \exists g^{-1}(x)$$

Note that if $M > N$ the pseudo-inverse function $g(x)^+ = (g(x)^Tg(x))^{-1}g(x)^T$ can be used instead of the inverse. Rather, given the system (38) and condition (39) holds, the control action that makes $e = 0$ a stable equilibrium is

$$u = g^{-1}(x)(-f(x) + x_C + \alpha e - \dot{D})$$

4. SPHERICAL UAV APPLICATION

The proposed control law is applied to the Spherical UAV
by computing the desired control effort with (29),(40) and
resolving the control allocation problem linearizing (5).

4.1 Single Integrator and Non Linear Control

The linear control law (29) can be applied to the motion equations (6), (7) because the inputs are directly inte-
 grated. From (6), the relation between $\mathbf{F}$ and $v_B$ is similar to a single integrator.

$$\frac{d}{dt} v_B = \frac{1}{m} \mathbf{F} - \omega \times v_B \approx k \cdot u + D$$

Likewise, from (7) the relation between $\mathbf{T}$ and $\omega$ is similar to a single integrator.

$$\frac{d}{dt} \omega = I_B^{-1}(\mathbf{T} - \omega I_B \omega) = I_B^{-1} \mathbf{T} - I_B^{-1} \omega I_B \omega \approx k \cdot u + D$$

Fig. 3. The variation of the disturbance estimation is
perpendicular to $L$.

3.4 Advantages of the proposed control action

As written in (29), the control action is

$$u = \frac{1}{k}(\dot{x}_C + \alpha e - \dot{D})$$

It is straightforward to understand that the control action is composed by three terms: a proportional action, a Feed
Forward and an estimation of the disturbance. Moreover, this kind of control doesn’t act like a Sliding Mode Control, so there is no chattering in the control action.

This characteristic generalizes the control structure, as it can be applied to any system that acts as a single integrator.

4.2 Commanded Variables and Control Allocation

The chosen control logic in this paper is the control of UAV
altitude and attitude, so the selected variables, depending of the data available from the sensors, are $x_{Int}$ or $x_{NL}$.

The plant can be considered as a ‘Single-Integrator’-like system if the state variables are $x_{Int}$, while it can be seen
as a NL-MIMO-AC when the state variables are $x_{NL}$. In both case, the commanded variables are $u_C$, as shown in
(44).

$$u_C = \begin{bmatrix} Z \\ L \\ M \\ N \end{bmatrix}, x_{Int} = \begin{bmatrix} u \\ p \\ q \\ r \end{bmatrix}, x_{NL} = \begin{bmatrix} \dot{p}_D \\ \phi \\ \theta \\ \psi \end{bmatrix}$$

Given $u_C$, the control allocation problem consists in finding
the set of inputs $u_R = [F \tau \alpha_1 \alpha_2]^T$ that reach the closest desired command (in norm). This is done linearizing and inverting equation (5), $f(u_R)$, around the current set of real input $u_{R_0}$.

$$u_C \approx f(u_R) \approx f(u_{R_0}) + \frac{\partial f}{\partial u_R} [u_{R_0} - u_{R_0}]$$

Inverting (45) yields

$$u_R = u_{R_0} + [\frac{\partial f}{\partial u_R}]_{u_{R_0}}^{-1} (u_C - f(u_{R_0}))$$

Note that the Jacobian is always full rank due to the
constraints in $u_R$ shown in Table 1.

4.3 External Loop

The proposed control method is applied when the con-
trolled variables are (generalised) velocities. In practical applications the command is in position or attitude, so
an outer loop is needed. Assuming that the internal loop behaves like a controlled 2nd order, as shown in Fig. 4, the outer controller can be synthesised with the linear control
theory: a P or PI could be sufficient, root locus, LQR and
so on. Note that the control actions given in (29) and (40)
(b) Nominal Plant

(c) Torque Disturbance

(c) Uncertainty and Disturbance

Fig. 5. System response for three simulation scenarios. Top: Adaptive Control. Bottom: Baseline PID Controller. The black dashed lines represent the commands.

\[
\begin{align*}
F_x & = \frac{1}{m} \dot{x}_x + \frac{1}{m} \Delta m \\
\dot{F}_x & = \dot{F}_x + \frac{1}{m} \Delta m \\
\end{align*}
\]

(47)

where \( \text{D}_{unc} = \frac{\Delta F_x \cdot \Delta m + \Delta F_x}{m \Delta m} \) represents the uncertainties due to \( \Delta m \) and \( \Delta F_x \). \( \text{D}_{flex} \) deals with the flexibility terms, \( \text{D}_{coupling} \) considers the channels interaction and \( \text{D}_{ext} \) is an external acceleration due to wind gusts or interactions with the external environment.

5. SIMULATION RESULTS

The effectiveness of the proposed control system is demonstrated through non-linear simulations. The UAV parameters used in simulations are taken from the prototype and shown in Table 1. The controlled variables are the Euler angles \( \eta \) with initial condition \( \eta_0 = [0 \ 0 \ 0]^T \). Moreover, a null-loop on \( \dot{P}_D \) is built in order to concentrate the effort on the attitude. The desired commands are the following:

\[
\begin{align*}
\phi_C & = \begin{cases} 
5 \text{deg} & t \leq 12 \\
10 \text{deg} & t > 12 
\end{cases} \\
\psi_C & = \begin{cases} 
5 \text{deg} & t \leq 6 \\
10 \text{deg} & t > 6 
\end{cases}
\end{align*}
\]

The control parameters are tuned as follows: the adaptive coefficients are all set as \( \eta_1 = \eta_2 = 2 \), and the proportional gain are \( [\alpha_{P_\phi}, \alpha_{P_\theta}, \alpha_{P_\psi}] = [5 \ 6 \ 6] \). For all channels the outer loop is a simple P controller with gain \( [k_\phi, k_\theta, k_\psi] = [2 \ 2 \ 4] \). The number of neurons used is 9, the RBF centers \( \mu_i \) are evenly spaced in \([-1 \ 1]\), and the widths \( \sigma_i \) are all 0.25. The performances are compared with a standard PI controller for the velocity, while the outer loop is the same.

5.1 Numerical results

The performance of the controller with the nominal plant is shown in Fig. 5a. As shown, the adaptive control system is much more decoupled and stable than the PI controller in the nominal case. In the second simulation, to check the disturbance rejection, a time-varying torque disturbance is added in the attitude channels. The total disturbance is shown in Fig. 7 and it is composed by a fixed term plus a time-varying disturbance. Fig. 5b shows that the angles error based on the proposed method is much more limited, about \( \pm 0.4 \) degrees than the PI method which has an error of about \( \pm 2 \) degrees.

### Table 1. UAV Data

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mass [kg]</td>
<td>( m )</td>
<td>0.596</td>
</tr>
<tr>
<td>Inertia Matrix ([Kg \cdot m^2])</td>
<td>( I_B )</td>
<td>( \begin{bmatrix} 3.9310 &amp; 6.0 &amp; -6.9 \ 6.0 &amp; 39.183 &amp; 47.1 \ -6.9 &amp; 47.1 &amp; 274.9 \end{bmatrix} )</td>
</tr>
<tr>
<td>Offset distance [m]</td>
<td>( d_V )</td>
<td>8.572 \cdot 10^{-3}</td>
</tr>
<tr>
<td>Force range [N]</td>
<td>( F )</td>
<td>( [0 \ 6.818 \ 7.6542] )</td>
</tr>
<tr>
<td>Torque range ([N \cdot m])</td>
<td>( \tau )</td>
<td>( [-0.0352 \ 0.0352] )</td>
</tr>
<tr>
<td>Angle range [rad]</td>
<td>( \alpha_{\phi} ), ( \alpha_{\theta} )</td>
<td>( [-0.3 \ 0.3] )</td>
</tr>
<tr>
<td>Motors time constant [s]</td>
<td>( \tau_m )</td>
<td>0.175</td>
</tr>
</tbody>
</table>

\[
\begin{align*}
\dot{\phi} & = \frac{1}{m} \phi & \dot{\theta} & = \frac{1}{m} \theta \\
\dot{\phi} & = \frac{1}{m} \dot{\phi} + \frac{1}{m} \Delta \phi \\
\end{align*}
\]
The relation between Aircraft, B., Lewis, F., and Johnson, E. (2015). Gui, H. et al. (2015). Attitude control of spherical Dixon, R. and Fernandez, Y. (2013). Design of a Spherical time-varying disturbances. the demonstration of the proposed control law in case of the proposed control scheme on different platforms and extensions include real test simulations, the application of is simple, easy to implement and quite effective. Further simulation results confirms that the proposed control method proven using the Lyapunov control theory. Numerical sim-server is designed based on a RBF-NN and the stability is certainties and external disturbances. The disturbance ob-developed for a Spherical UAV in the presence of model un- In this paper, an on-line adaptive control scheme is de-recover easily the steady state condition after the fault. 6. CONCLUSION In this paper, an on-line adaptive control scheme is de-veloped for a Spherical UAV in the presence of model uncertainties and external disturbances. The disturbance ob-server is designed based on a RBF-NN and the stability is proven using the Lyapunov control theory. Numerical sim-ulation results confirms that the proposed control method is simple, easy to implement and quite effective. Further extensions include real test simulations, the application of the proposed control scheme on different platforms and the demon-tration of the proposed control law in case of time-varying disturbances.

REFERENCES

Appendix A. NL-MIMO-AC, POSITION
The relation between \( v_B \) and \( v_E \) is (9). Deriving the inverse of (9) it holds

\[
\dot{v}_B = D\dot{C}Mv_E + DCM\dot{v}_E \tag{A.1}
\]

Substituting (A.1) in (41) and expliciting \( \dot{v}_E \) yields

\[
\frac{d}{dt} v_E = DCM^T \frac{1}{m} F - DCM^T D\dot{C}Mv_E + \ldots
\]

\[\ldots - DCM^T (J^{-1}\dot{\eta}) \times (DCMv_E) - [0 0 g]^T \tag{A.2}\]

Equation (A.2) is in form (38), where

\[
f = -DCM^T D\dot{C}Mv_E - DCM^T (J^{-1}\dot{\eta}) \times (DCMv_E) \tag{A.3}
\]

\[D = -[0 0 g]^T \tag{A.4}\]

And the map \( g = DCM^T \frac{1}{m} \) has always rank = 3.

Appendix B. NL-MIMO-AC, ATTITUDE
The relation between \( \omega \) and \( \eta \) is (8). Deriving the inverse of (8) it holds

\[
\dot{\omega} = \left( \frac{d}{dt} J^{-1}\right) \dot{\eta} + J^{-1} \dot{\eta} \tag{B.1}
\]

Where

\[
\frac{d}{dt} J^{-1} = \begin{bmatrix}
0 & 0 & -c_\phi \dot{\theta} \\
0 & -s_\phi c_\theta \dot{\phi} - s_\phi s_\theta \dot{\theta} & -c_\phi s_\theta \dot{\phi} - c_\phi s_\theta \dot{\theta} \\
0 & c_\phi \dot{\phi} - s_\phi c_\theta \dot{\phi} - s_\phi s_\theta \dot{\theta} & 0
\end{bmatrix} \tag{B.2}
\]

Substituting (B.1) and (8) in (42) and expliciting \( \dot{\eta} \) yields

\[
\frac{d}{dt} \ddot{\eta} = JJ_B^{-1}T - J \left( \frac{d}{dt} J^{-1}\right) \dot{\eta} + I_B^{-1} \left( (J^{-1}\dot{\eta}) \times (I_B J^{-1}\dot{\eta}) \right) \tag{B.3}
\]

Equation (B.3) is in the form (38), where

\[
f(\eta, \dot{\eta}) = -J \left( \frac{d}{dt} J^{-1}\right) \dot{\eta} + I_B^{-1} \left( (J^{-1}\dot{\eta}) \times (I_B J^{-1}\dot{\eta}) \right) \tag{B.4}
\]

\[g(\eta, \dot{\eta}) = JJ_B^{-1} \Rightarrow g^{-1} = I_B J^{-1} \tag{B.5}\]

Note that rank \( g^{-1} = 3 \) is ensured if \( \theta \neq \pm \frac{\pi}{2} \) and the inertia matrix \( I_B \) is diagonal; the condition must be checked in all the other cases.
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