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Original Article

Hover Control for Helicopter Using Neural Network-Based Model Reference Adaptive Controller

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Abstract: *Unmanned aerial vehicles (UAV), have enormous important application in many fields. Quanser three degree of freedom (3-DOF) helicopter is a benchmark laboratory model for testing and validating the validity of various flight control algorithms. The elevation control of a 3-DOF helicopter is a complex task due to system nonlinearity, uncertainty and strong coupling dynamical model. In this paper, an RBF neural network model reference adaptive controller has been used, employing the grate approximation capability of the neural network to match the unknown and nonlinearity in order to build a strong MRAC adaptive control algorithm. The control law and stable neural network updating law are determined using Lyapunov theory.*

***Index Terms*— Neural Network, Model Reference Adaptive Control, Bench-top Helicopter, Model Uncertainties.**

I. Introduction

UAV control system has greatly improved in the recent years, with the modern technological advance in the computer applications and control theory. There are many difficulties in developing a high performance controller for an unmanned aerial vehicles; due to parametric uncertainty, nonlinearity, under actuation and strong coupling. To overcome these challenges a numerous control algorithm have been suggested to control the attitude of the UAV, in [1] the yaw control of the UAV has studied using the robust H_2 control algorithm. A pitch motion control using neural network-based adaptive feedback proposed in [2]. A sliding mode controller is proposed to improve the tracking performance and error elimination in [3, 4], however sliding mode controller exhibits a chattering phenomenon due to the existence of switching logic in the control law. A hybrid control combining the integral action and the backstepping nonlinear algorithm proposed by W. Gao and Z. Fang in [5] and L. Junfang and et al in [6]. However the main drawbacks for these methods is that the parameter estimation is growing and depending on the initial conditions of the UAV [7].

In addition a model-based fuzzy control nested saturation control was applied in [8]. A single input interval type-2 fuzzy PID controller and an analytical approach to construct the footprint of the uncertainty of the IT2 fuzzy set is applied in [9]. Neural network offer an advantage over other form of control algorithms, where the nonlinear mapping ability of the neural network is employed for forward and inverse plant modeling. In this paper, a neural network-based model reference adaptive controller has been applied to control the elevation angle of a 3-DOF helicopter. The error between the plant output and the reference model is used to adjust the controller parameters. To compensate the plant nonlinearity the RBF neural network is exploited in the control law. The learning law is obtained using Lyapunov theory. Moreover the whole system stability has been proved.

This paper is organized as follows. In section **II** the helicopter system is described and the dynamic model is established. The neural network model reference controller is designed in section **III**. The simulation results are shown in section **IV** and conclusions are given in section **V**.

II. HELICOPTER SYSTEM DYNAMICS

A three degree of freedom (3-DOF) bench-top helicopter from Quanser Inc. is shown as a physical model and free body diagram in Fig. 1 and Fig. 2 respectively. Two DC motors with propellers mounted on a rectangular structure can generate a force proportional to the applied voltages. The motors are aligned parallel and the thrust generated is normal to the structure. The total generated aerodynamic force F makes the helicopter body to rotate around an angle measured by an absolute encoder. The helicopter structure can rotate about a suspension point at end of a long beam. The beam is gimballed on a 2-DOF equipped joint and can freely yaw and pitch [10]. The second end of the arm connected to a counterweight mass M_w so that the total effective mass of the helicopter M is lighter to be lifted off the ground by the aerodynamic force of the motors. If the front motor supplied by a positive voltage the body will swivel in the positive pitch direction, while a negative pitch will occur if the second motor is supplied. If either motor supplied by a positive voltage this causes an elevation of the body. A trust vectors generated due to body pitch; results in a travel of the body [10]. The dynamics of the elevation angle ε is determined using Lagrange's equations [11] such that:

$$\ddot{\varepsilon} + \frac{b_\varepsilon}{J_\varepsilon}\dot{\varepsilon} + \frac{Mg}{J_\varepsilon}[(h+d)\sin\varepsilon + \cos\varepsilon] + \frac{M_w g}{J_\varepsilon}(l_2 + l_2\cos\alpha)\cos\varepsilon + \frac{M_w\, g}{J_\varepsilon}(l_3\sin\varepsilon - h)\sin\varepsilon = \ l_1\, F(t) \quad (1)$$

Which can be written in the following form

$$\ddot{\varepsilon} + f(\varepsilon, \dot{\varepsilon}) = l_1\, F(t) \quad (2)$$

where $f(\varepsilon, \dot{\varepsilon})$ is unknown nonlinear part of the helicopter dynamics.

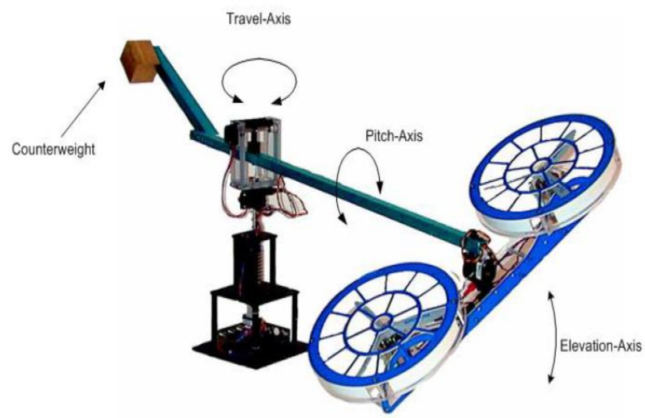

Fig. 1 Physical Model of Quanser 3-DOF Helicopter

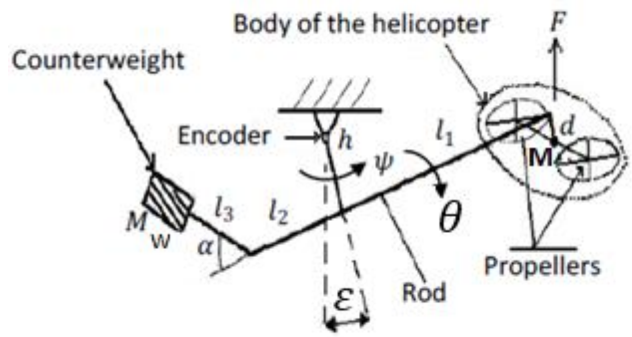

Fig. 2 Free Body Diagram of Quanser 3-DOF Helicopter

The parameters of the helicopter are described as follows:

M	: Total mass of both motors.
M_w	: Mass of the counter weight.
b_ε	: Dynamic coefficient.
J_ε	: Inertial moment of the whole system around the elevation angle.
l_1	: Distance between travel axis to the helicopter body.
l_2	: Distance between travel axis to the counter weight arm.
h, d, l_3	: Are length in [m] as shown in Fig. 2
F	: Total force
θ	: Pitch motion angle.
ε	: Roll motion angle.
ψ	: Yaw motion angle.
α	: Fixed construction angle.

In this paper, a neural network model reference adaptive controller (NN MRAC) will be designed so that the elevation angle behavior follow the predefined reference model as below:

$$\ddot{\varepsilon}_m + a_m\dot{\varepsilon}_m + b_m\varepsilon_m = k_m\varepsilon_d \quad (3)$$

where a_m, b_m and k_m are pre-specified design parameters and ε_m specifies the desired system performance for the UAV elevation angle, and ε_d is the desired angle.

III. Neural Network-Based MRAC Design

The goal of the designed algorithm is to obtain a control law and the learning law of the controller paramters, in such away the UAV plant responds dynamically as the specified reference model so that:

$$\lim_{t\to\infty}|\varepsilon(t) - \varepsilon_m(t)| \le \epsilon \quad (4)$$

where $(\epsilon < 0)$ is a specified constant.
The presented nonlinear controller is a generalization [12] of the well known liner model reference adaptive controller system [13, 14].
Consider the system model given by (1), and the reference model given by (3) then, the proposed controller shown in Fig. 3, has the following form:

$$F(t) = \frac{1}{l_1}\left[-b_m\varepsilon(t) - a_m\dot{\varepsilon}(t) + k_m\varepsilon_m(t) + \hat{f}(\boldsymbol{x}, \Theta(t))\right] \quad (5)$$

where $\hat{f}(\boldsymbol{x}, \Theta(t))$ is the RBF neural network output that will approximate the unknown function $f(\varepsilon, \dot{\varepsilon})$ and defined by

$$\hat{f}(\boldsymbol{x}, \Theta(t)) = \sum_{i=1}^{N} \theta_i \exp\left(\frac{\|x - c_i\|}{2\,\sigma_i^2}\right) \quad (6)$$

where $\boldsymbol{x}$ is the neural network inputs vector and N is the number of neurons in the hidden layer.
And $\Theta(t)$ is the estimate weights vector. The activation functions chosen for the neural network are the Gaussian radial basis functions with the following paramters c_i and σ_i are the mean and standard deviation respectively. The RBF neural network structure used in this paper is shown in Fig. 4.

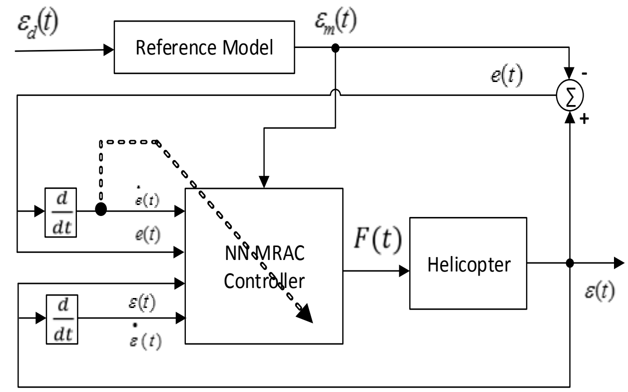

Fig. 3 The Proposed NN MRAC

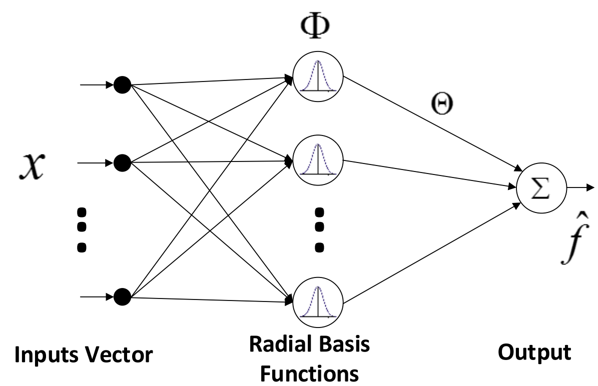

Fig. 4 The RBF NN Structure

The error between the helicopter elevation angle the reference model output used to train the RBF neural network as below:

$$e(t) = \varepsilon(t) - \varepsilon_m(t) \quad (7)$$

When the RBF neural network exactly match the unkown part of the system, the closed loop error dynamic equation can be written as follows:

$$\ddot{e}(t) + a_m\dot{e}(t) + b_m e(t) = 0 \quad (8)$$

It is clear that (7) is asymptotically stable for all $a_m > 0$ and $b_m > 0$. If we define

$$\tilde{f}(\boldsymbol{x}, \Theta) = \hat{f}(\boldsymbol{x}, \Theta(t)) - f(\boldsymbol{x}) \quad (9)$$

Then, for driving the helicopter to response dynamically as the specified reference model , the weights values of the RBF NN will be adjusted using an appropriate updating law. If $\Theta \in R^N$ is the current weight estimate vector and Θ^* is the optimal weights vector then,

$$\widetilde{\Theta}(t) = \Theta(t) - \Theta^* \quad (10)$$

where $\widetilde{\Theta}(t)$ is the weights deviation or weights estimation error vector. As the error between the unknown function $f(\boldsymbol{x})$ and the RBF neural network output $\hat{f}(\boldsymbol{x}, \Theta(t))$ is not accessible, an alternative approch using the error between the plant output and the reference model is used to generate the learning law for the proposed controller. To prove the stability and derive the NN weights updating law, Lyaponouv theory based on the background material in [12, 15] is employed as follow:
Assume that the RBF neural network output is given in matrix form as below:

$$\hat{f}(\boldsymbol{x}, \Theta(t)) = \Theta^T(t)\, \Phi(\boldsymbol{x}, t) \quad (11)$$

where $\Phi(\boldsymbol{x}, t) \in R^N$ is the radial basis functions output vector. Assume that Ψ and K are diagonal positive definite matrices, and the defined Lyaponov function has the following form:

$$V\left(e, \widetilde{\Theta}(t)\right) = \frac{1}{2} b_m e^2(t) + \frac{1}{2}\dot{e}^2(t) + \frac{1}{2}\widetilde{\Theta}^T(t)\Psi^{-1}\widetilde{\Theta}(t) \quad (12)$$

Then the time derivative of $V\left(e, \widetilde{\Theta}(t)\right)$ is

$$\dot{V}\left(e, \widetilde{\Theta}(t)\right) = b_m e\, \dot{e} + e\, \dot{e} + \widetilde{\Theta}^T \Psi^{-1} \dot{\widetilde{\Theta}}(t) = -a_m \dot{e}^2 + \tilde{f}(\mathbf{x}, \Theta)\, \dot{e} + \widetilde{\Theta}^T \Psi^{-1} \dot{\widetilde{\Theta}}(t) \quad (13)$$

Assume that the learning law is given by:

$$\dot{\Theta}(t) = -\Psi\, \Phi(\boldsymbol{x}, t)\, \dot{e}(t) - K\ \Theta(t) \quad (14)$$

Then (13) can be written in the following form:

$$\dot{V}\left(e, \widetilde{\Theta}(t)\right) = -\left[a_m - \frac{1}{2\eta^2}\right]\dot{e}^2 - \left[\mu_1 - \frac{\mu_2}{2\zeta^2}\right]\left\|\widetilde{\Theta}(t)\right\|^2 + \frac{1}{2}\left(\eta^2\left|\tilde{f}(\boldsymbol{x}, \Theta^*)\right|^2 + \mu_2\zeta^2\|\Theta^*\|^2\right. \quad (15)$$

where
$\mu_1 = \min_{i}\{K_i / \Psi_i\}$
$\mu_2 = |\Psi^{-1}K|$
η and $\zeta \in R$

It is usually possible to select $\eta^2 > 1/2a_m$ and $\zeta^2 > \mu_2/2\mu_1$; this implies that (8) has strong practical stability.

IV. Simulation Results

This section presents the results of a numerical simulation of the proposed neural network based model reference adaptive controller performed to evaluate the hover controlling of a bench-top helicopter and verify the stability of the system and the learning law.

The helicopter system parameters has the following values listed in Table. 1

Parameter	Value	Unit
M	1.426	[Kg]
M_w	1.870	[Kg]
J_ε	1.200	[Nms^2]
l_1	0.200	[m]
l_2	0.060	[m]
l_3	0.185	[m]
d	0.070	[m]
h	0.020	[m]
g	9.810	[m/s^2]

Table.1 Helicopter System Parameters

The reference model is designed such as $a_m = 9$, $b_m = 16$ and $k_m = 1$.

The RBF neural network has 12 neurons for each input with the following parameters:

Initial output weights vector $\widehat{\Theta}(0)$ are set to 0.5 and standard deviation vector σ are set to 2. Gaussian membership function mean values which are evenly distributed, are given below for the two inputs:

$C = [i, i]^T$ where $i = -2.5,\ -2,\ -1.5,\ -1, 0.5,\ -0.25,\ 0.25,\ 0.5,\ 1,\ 1.5,\ 2,\ 2.5.$

$\Psi = 19.2\,\boldsymbol{I}$ and $K = 0.05\,\boldsymbol{I}$ where $\boldsymbol{I}$ is an identity diagonal matrix with proper dimensions.

All the initial values of the system and the reference model are set to zero. Fig. 5 (a) - (c) shows the simulation results for elevation angle tracking as a square wave input. The solid line represent the actual output; the dashed line represent the reference model output. Fig. 6 (a) - (c) shows the simulation results for elevation tracking as sine wave input. The solid line represent the actual output; the dashed line represent the reference model output.

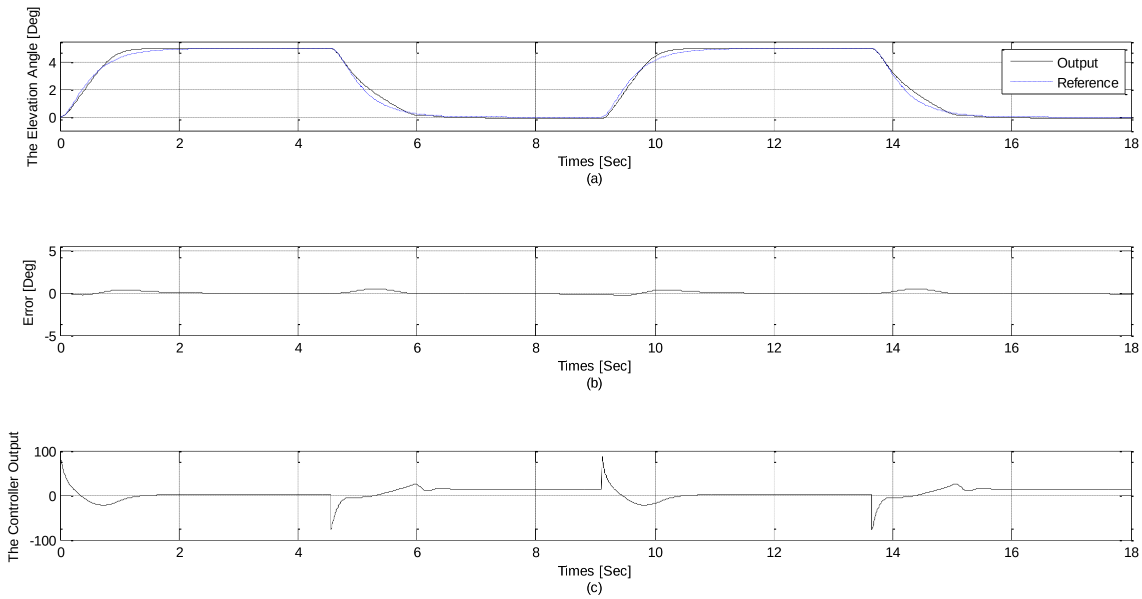

Fig. 5 (a) The Helicopter elevation angle. (b) The output tracking error. (c) Controller output.

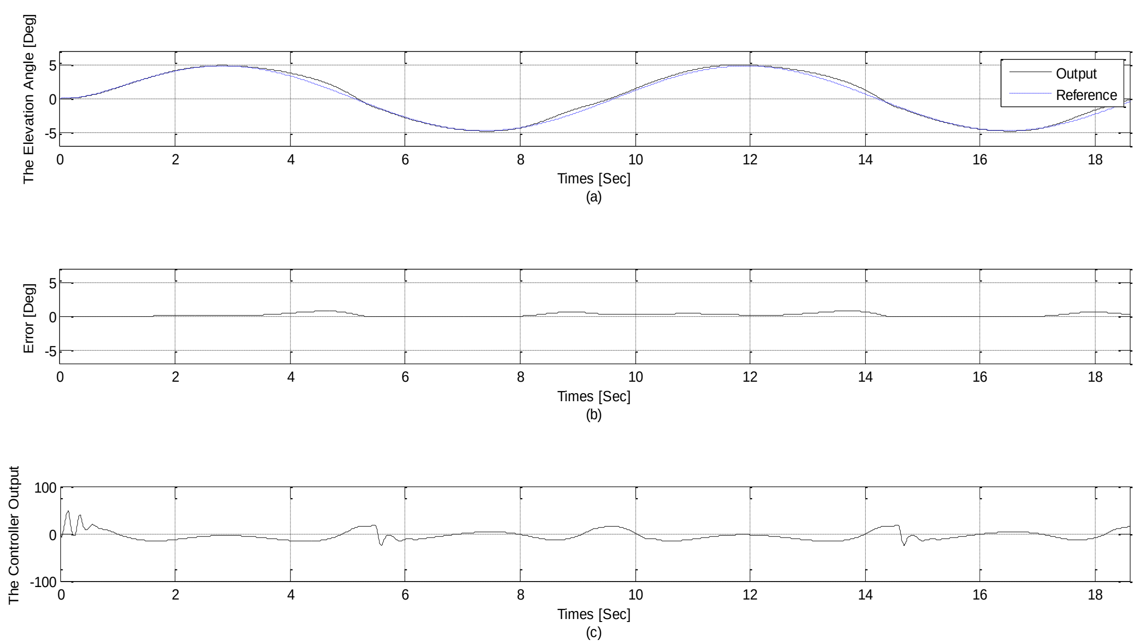

Fig. 6 (a) The Helicopter elevation angle. (b) The output tracking error. (c) Controller output.

V. CONCLUSION

A neural network-based model reference adaptive controller (NN MRAC) was proposed for controlling the elevation angle of a bench-top helicopter from Quanser Inc. The RBF neural network has been adaptively learned the helicopter uncertainty and nonlinear dynamics, then its output used as a part in the control law to compensate the system nonlinearity. Including Lyapunov stability theory in designing the RBF NN and selecting the optimal weights, enables the use of the proposed control law and ensures stability and robustness of the hovering system. Simulation results show that the proposed NN MRAC can efficiently solve the helicopter elevation angle problem.

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