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NEURO-ADAPTIVE TRAJECTORY CONTROL OF UNMANNED AERIAL VEHICLES

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Abstract: *A neuro-adaptive approach for autonomous flight controller design for aerial robots is proposed. Three intelligent modules are implemented to control respectively the altitude, airspeed and roll angle of the airplane, through which the altitude and the latitude-longitude of the unmanned aerial vehicle are controlled. Each intelligent module consists of a conventional feedback controller and a neural network feedback controller. The former is provided both to guarantee global asymptotic stability in compact space and as an inverse reference model of the response of the controlled system. The proposed approach makes direct use of the variable structure systems theory. A variable structure systems-based on-line learning algorithm is developed and applied to the neural network controller. Results from simulated trajectory control of the Aerosonde unmanned aerial vehicle by using the proposed neuro-adaptive control scheme are presented.*

I. Introduction

The main purpose of the autopilot is to enable the unmanned aircraft to accomplish its mission autonomously, without any (or with minimal) intervention from the human operator. Three hierarchical levels of control can be usually identified in the modern unmanned aerial vehicle (UAV) autopilot systems: (i) Low-level control include control and stability loops aiming to provide airplane with improved dynamic stability, regulation of flight parameters, as well as tracking of basic autopilot commands; (ii) Mid-level control provides navigation and guidance capability to the take-off and landing, climb, cruise, and loiter; (iii) High-level control has to interpret the mission objectives and safety constraints, awareness of the current aircraft and environment conditions.

The most widely used approach at the autopilot low-level control, currently still implements conventional PI and PID controllers, augmented with online gain scheduling [1]. The increasing complexity of today's aircraft dynamical systems which is frequently coupled with unknown dynamics, modeling errors, various sorts of disturbances, uncertainties, and noise creates a need for advanced control design techniques that are able to overcome limitations on the traditional feedback control. During the last decade model-free, computationally intelligent techniques using either fuzzy logic or neural networks (NNs) have been investigated in order to circumvent existing difficulties in the autopilot low-level control [2-4].

The present paper addresses the design of adaptive neural network feedback controllers for the low level control loops of the UAV autopilot system. A variable structure systems-based (VSS-based) on-line learning algorithm is developed and applied to the proposed neurocontrollers.

The paper is organized as follows. Section II starts with a basic introduction to the proposed neuro-adaptive control approach and then explains the design of the intelligent controllers used for the trajectory control of the UAV. The variable structure systems-based online learning approach for continuous time neural networks is introduced in Section III. Section IV is devoted to the obtained results from simulations, and the concluding remarks are given in Section V.

II. The Neuro-Adaptive Control System

The approach proposed in this paper is based on the design of three neuro-adaptive control modules. Among them, one module has to adjust the aircraft bank angle value in order to control the latitude and longitude coordinates, and the other two modules are used to adjust the elevator and throttle controls of the UAV in order to obtain the desired altitude value. These intelligent control modules acting in combination enable simple navigation of the unmanned aerial vehicle.

The so-called feedback-error-learning concept, proposed in [5] and initially applied to control of robot manipulators, has been used to tune online the proposed neurocontrollers. The general structure of an intelligent control module is shown on Fig. 1. It relies on the parallel work of two feedback controllers - a neural network feedback controller (NNFC) and a conventional feedback controller (CFC). It is common, when applying the feedback-error-learning concept, to assume that a proportional plus derivative (PD) controller is used as CFC. It serves both to guarantee global asymptotic stability in compact space and as an inverse reference model of the response of the system under control. The output of the CFC is used as an error signal to update the weights of the neurocontroller in and in this way the latter is learning online to eliminate the conventional controller from the control of the system. The weakness of the approach based on the usage of a PD controller (and also of the obtained in this way PD-type NNFC) is that in many cases it is not possible to remove out the steady state error.

When the required control performance cannot be reached by using a PD control law, then proportional plus integral (PI) or proportional plus derivative plus integral (PID) controllers can be used as CFC (thus adaptive PI-type, or PID-type neurocontrollers can be obtained respectively). The latter approach has been adopted and implemented in this investigation by adding one common for both (CFC and NNFC) blocks integrating term, placed after the summing junction for the output signals from the two controllers (see Fig. 1).

Due to the highly nonlinear nature of UAV dynamics and the inference between the controlled parameters two PI-type adaptive NNFCs have been constructed in this work for the bank angle and altitude controller respectively (by implementing only P terms in the CFC blocks) and one PID-type neuro-adaptive controller has been utilized to control the airspeed.

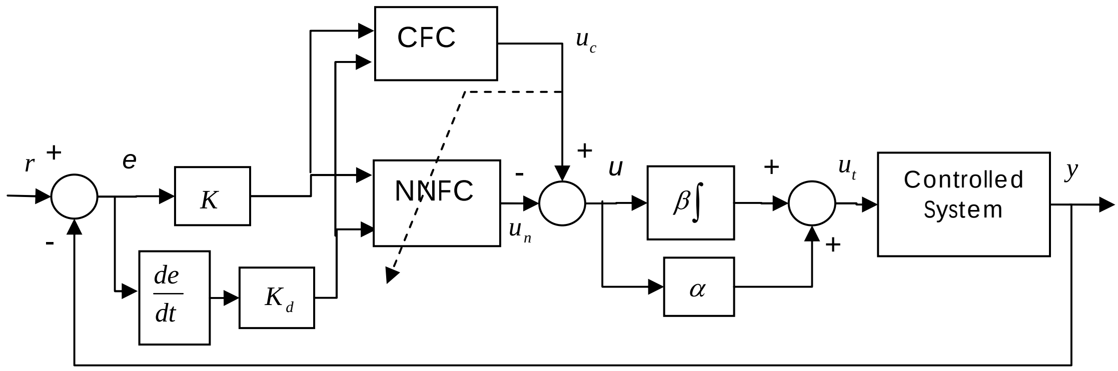

Fig. 1. Block diagram of the implemented feedback-error-learning scheme for a PID-type adaptive neurocontroller.

III. The Sliding Mode Online Learning Approach

Most of the existing online training methods for NNs rely on the gradient descent methodology and involve the computation of partial derivatives, or sensitivity functions. In this respect, they can be considered as extensions of the well-known backpropagation algorithm for multilayer feedforward NNs and hence they inherit some of its major drawbacks among which, in particular, is the difficulty to obtain analytical results concerning the convergence and stability of the learning schemes.

An alternative way to design a robust learning scheme is to utilize the VSS theory [6] in constructing the parameter adaptation mechanism of the NNs since the robustness of the variable structure control (VSC) scheme against unmodelled dynamics, disturbances, time delays and nonlinearities is well known [7].

Consider the two-layered feedforward NN with a scalar output, implemented as a neural network feedback controller. The following definitions will be used:

$X(t)=\left[x_1(t),\ \dots\ x_p(t)\right]^T$ - vector of the time-varying input signals augmented by the bias term.

$U_H^n(t)=\left[u_{H1}^n(t),\dots,u_{Hn}^n(t)\right]^T$ - vector of the output signals of the neurons in the hidden layer.

$u^n(t)$ - scalar signal representing the time-varying output of the network.

$W1(t)_{(n\times p)}$ - matrix of the time-varying connections' weights between the neurons in the input and the hidden layer, where each matrix's element $w1_{ij}(t)$ denotes the weight of the connection of the neuron i from its input j.

$W2(t)_{(1\times n)} = \left[w2_1(t),...,w2_n(t)\right]$ - vector of the connections' weights between the neurons in the hidden layer and the output node. Both $W1(t)_{(n\times p)}$ and $W2(t)_{(1\times p)}$ are considered augmented by including the bias weight components for the neurons in the hidden layer and the output neuron respectively.

$f(\cdot)$ - nonlinear, differentiable, monotonously increasing activation function of the neurons in the hidden layer of the network (e. g. log-sigmoid or tan-sigmoid function). The derivative of the activation function $f(\cdot)$ of the neuron i from the hidden layer is denoted as $A_i(t)$ where

(1) $$0 < A_i(t) = \frac{d}{dt}\left[f\left(\sum_{j=1}^{p} w1_{ij} x_j\right)\right] \le B_A \ \forall i, j$$

and B_A corresponds to its maximum value.

The neuron in the output layer is considered with a linear activation function.

The output signal $u_{H_i}^n$ of the i-th neuron from the hidden layer and the output signal of the network $u^n(t)$ are defined respectively as follows:

(2) $$u_{H_i}^n = f\left(\sum_{j=1}^{p} w1_{ij} x_j\right) = f\left(W1_i X\right)$$

(3) $$u^n(t) = \sum_{i=1}^{n} w2_i u_{H_i}^n = W2U_H^n$$

The NNFC is assumed to operate within the feedback-error-learning scheme, the general structure of which is presented on Figure 1. It will be assumed (due to the existence of a CFC controller in the scheme) that the input vector of the NNFC and its time derivative are bounded, i.e.

(4) $$\left\|X(t)\right\| = \sqrt{x_1^2(t) + ... + x_p^2} \le B_X \ \forall t$$

(5) $$\left\|\dot{X}(t)\right\| = \sqrt{\dot{x}_1^2(t) + ... + \dot{x}_p^2(t)} \le B_{\dot{X}} \ \forall t$$

with B_X and $B_{\dot{X}}$ being known positive constants.

Due to the physical constraints, it is also assumed that the magnitude of all vectors row $W1_i(t)$ constituting the matrix $W1(t)$ and the elements of the vector $W2(t)$ are bounded, i.e.

(6) $$\left\|W1_i(t)\right\| = \sqrt{w1_{i1}^2(t) + w1_{i2}^2(t) + ... + w1_{ip}^2(t)} \le B_{W1} \ \forall t$$

(7) $$\left|w2_i(t)\right| \le B_{W2} \ \forall t$$

for some known constants B_{W1} and B_{W2}, where $i = 1, 2, ..., n$.

$u(t)$ and $\dot{u}(t)$ are also considered as bounded signals, i.e.

(8) $$\left|u(t)\right| \le B_u, \quad \left|\dot{u}(t)\right| \le B_{\dot{u}} \ \forall t$$

where B_u and $B_{\dot{u}}$ are positive constants.

A VSC-based on-line learning algorithm is applied to the NNFC in this investigation. The zero adaptive learning error level for the controller $s_c\left(u, u^n\right)$ is defined as follows:

(9) $$s_c\left(u^n, u\right) = u^c = u^n + u$$

with λ being a constant determining the slope of the sliding surface.

Definition 1. A sliding motion will have place on a sliding surface $s_c\left(u^n, u\right) = u^c(t) = 0$, after a hitting time t_h, if the condition $s_c(t)\dot{s}_c(t) = u^c(t)\dot{u}^c(t) < 0$ is satisfied for all t in some nontrivial semi-open subinterval of time of the form $\left[t, t_h\right) \subset \left(-\infty, t_h\right)$.

The learning algorithm for the NNFC weights $W1(t)$ and $W2(t)$ has to be derived in such a way that the sliding mode condition of definition 1 will be enforced.

Let us denote as "$sign(s_c)$" the signum function, defined as follows

(10) $$sign(s_c)=\begin{cases}1 & for\ s_c(t)>0\\ 0 & for\ s_c(t)=0\\ -1 & for\ s_c(t)<0\end{cases}$$

To enable $s_c=0$ is reached, the following theorem is introduced.

Theorem 1. If the adaptation law for the weights $W1(t)$ and $W2(t)$ of NNFC is chosen respectively

(11) $$\dot{w}1_{ij}=-\left(\frac{w2_i x_j}{X^T X}\right)\alpha sign(s_c);\quad \dot{w}2_i=-\left[\frac{u_{H_i}^n}{\left(U_H^n\right)^T U_H^n}\right]\alpha sign(s_c)$$

with α being sufficiently large positive constant satisfying $\alpha>nB_A B_{W1}B_{\dot{X}}B_{W2}+B_{\dot{u}}$ then, given an arbitrary initial condition $s_c(0)$, the learning error $u^c(t)$ will converge to zero during a finite time t_h which may be estimated as

(12) $$t_h\le\frac{|s_c(0)|}{\alpha-nB_A B_{W1}B_{\dot{X}}B_{W2}+B_{\dot{u}}}$$

and a sliding motion will be maintained on $u^c=0$ for all $t>t_h$.

Proof. Consider $V_c=\frac{1}{2}s_c^2$ as a Lyapunov function candidate. Then differentiating V_c yields:

$$\dot{V}_c=s_c\left(\dot{u}^n+\dot{u}\right)=s_c\left\{\frac{d}{dt}\left[\sum_{i=1}^{n}w2_i\, f\left(\sum_{j=1}^{p}w1_{ij}x_j\right)\right]+\dot{u}\right\}=s_c\left[\sum_{i=1}^{n}\dot{w}2_i u_{H_i}^n+\sum_{i=1}^{n}w2_i A_i\sum_{j=1}^{p}\left(\dot{w}1_{ij}x_j+w1_{ij}\dot{x}_j\right)+\dot{u}\right]=$$

$$=s_c\left\{-\sum_{i=1}^{n}\frac{u_{H_i}^n}{U_H^T U_H}\alpha sign(s_c)u_{H_i}^n+\sum_{i=1}^{n}A_i\sum_{j=1}^{p}\left[-\left(\frac{w2_i x_j}{X^T X}\right)\alpha sign(s_c)x_j w2_i+w1_{ij}\dot{x}_j w2_i\right]+\dot{u}\right\}=$$

$$=s_c\left[-\alpha sign(s_c)-\sum_{i=1}^{n}A_i\alpha w2_i^2 sign(s_c)+\sum_{i=1}^{n}A_i w2_i\sum_{j=1}^{p}w1_{ij}\dot{x}_j+\dot{u}\right]=$$

$$=-\left(\alpha+\alpha\sum_{i=1}^{n}A_i w2_i^2\right)|s_c|+\left(\sum_{i=1}^{n}A_i w2_i\sum_{j=1}^{p}w1_{ij}\dot{x}_j+\dot{u}\right)s_c\le-\alpha|s_c|+s_c\left(\sum_{i=1}^{n}A_i w2_i\sum_{j=1}^{p}w1_{ij}\dot{x}_j+\dot{u}\right)\le$$

(13) $$\le-\alpha|s_c|+\left(nB_A B_{W2}B_{W1}B_{\dot{X}}+B_{\dot{u}}\right)|s_c|=|s_c|\left(-\alpha+nB_A B_{W2}B_{W1}B_{\dot{X}}+B_{\dot{u}}\right)<0\quad\forall s_c\ne0$$

where $A_i(t)$, $0<A_i(t)=\frac{d}{dt}\left[f\left(\sum_{j=1}^{p}w1_{ij}x_j\right)\right]\le B_A\ \forall i,j$ is the derivative of the neurons' activation function $f(\cdot)$, and B_A corresponds to its maximum value.

The inequality (13) means that the controlled trajectories of the learning error $s_c(t)$ converge to zero in a stable manner. The convergence will takes place in finite time which is estimated by eq. (12) (see prove in [7]).

IV. Simulation Results

The effectiveness of the proposed sliding mode neuro-adaptive control approach has been tested by implementing simultaneously the three low-level control loops under investigation for the trajectory tracking control of airplane. A standard configuration of MATLAB/SIMULINK by The Mathworks, Inc. and the Aeronautical Simulation Block Set (AeroSim) [8], have been used as development platform for the flight control system design. The dynamic model of the Aerosonde UAV [9] has been utilized for the conducted tests. Additionally, to ease the design process, the Microsoft Flight Simulator has been used to get visual outputs about the flight of the Aerosonde UAV and to see its physical response. A number of studies were carried out for different flight scenarios. For the results reported in this paper, a worst case approach was adopted, in which the reference signals for all the controlled variables are allowed to change simultaneously. The reference trajectories used for the simulation studies are given below, where $X_{d1}(t)$, $X_{d2}(t)$, and $X_{d3}(t)$ are the desired bank angle, speed and altitude, respectively.

$$[X_d] = \begin{bmatrix} X_{d1}(t) \\ X_{d2}(t) \\ X_{d3}(t) \end{bmatrix} = \begin{bmatrix} 10\sin(0.022\pi t) \\ 23 + 5\sin(0.01\pi t) \\ 1000 + 50\sin(0.02\pi t) \end{bmatrix} \quad (14)$$

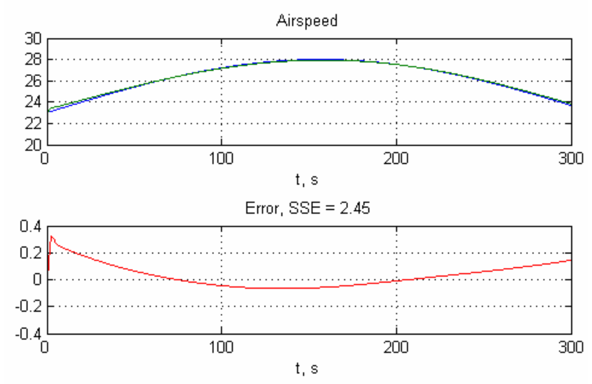

Fig. 2. Airspeed tracking and tracking error with conventional PID controller.

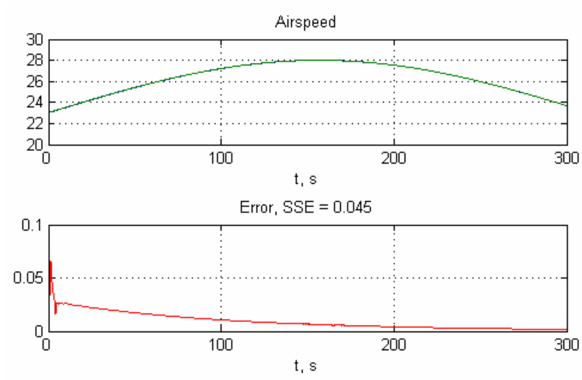

Fig. 3. Airspeed tracking and tracking error with the proposed PID-type neuro-adaptive control scheme.

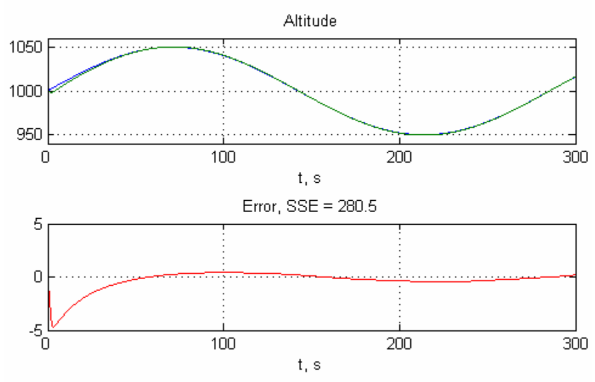

Fig. 4. Altitude tracking and tracking error with conventional PI controller.

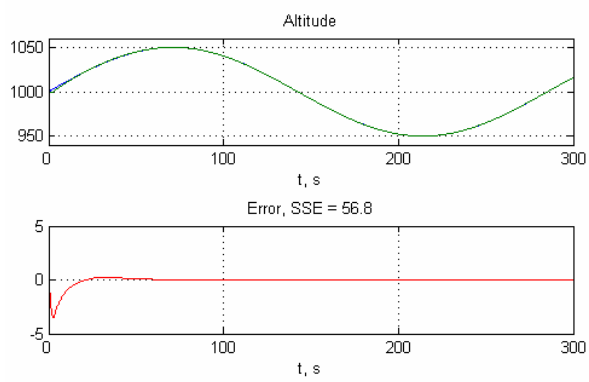

Fig. 5. Altitude tracking and tracking error with the proposed PI-type neuro-adaptive control scheme.

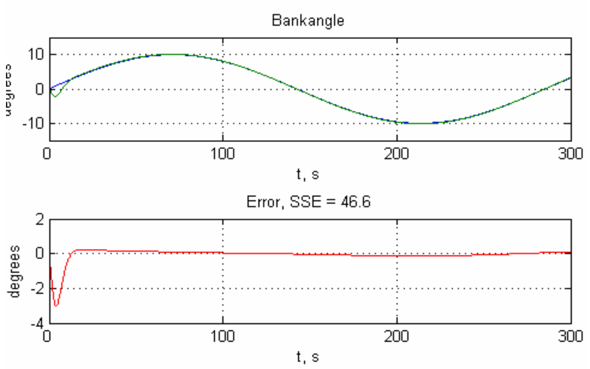

Fig.6. Bank angle tracking and tracking error with conventional PI controller.

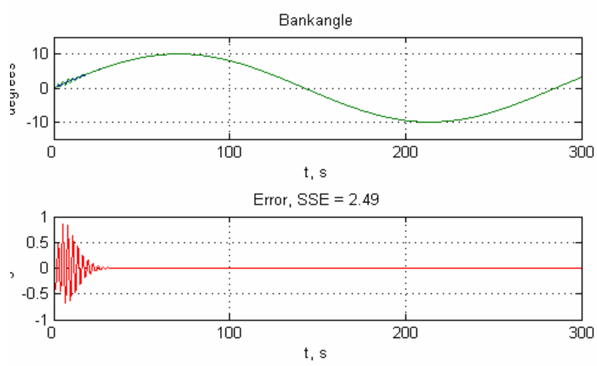

Fig. 7.Bank angle tracking and tracking error with the proposed PI-type neuro-adaptive control scheme.

In order to evaluate the performance of the proposed neuro-adaptive control schemes, similar simulation studies were carried out with well tuned conventional PI controllers (PID in case of elevator control). The tracked desired values of the airspeed, altitude and bank angle and the corresponding tracking errors when conventional controllers are used alone and with the proposed neuro-adaptive controllers are presented on Figures 2, 4, 6 and Figures 3, 5, 7 respectively. As it can be seen from the results the sum-squared values of the tracking errors when the proposed intelligent control modules are used are by order of magnitude smaller than those of the conventional controllers working alone.

V. Conclusion

A novel approach for design of model-free adaptive neural network feedback controllers for the low level control loops of UAV autopilot is introduced. The controlled system is under a closed-loop simultaneously with two controllers: a conventional controller and an adaptive variable structure neural network controller. Results obtained from a simulated trajectory control of Aerosonde unmanned aerial vehicle demonstrate the feasibility of the sliding mode learning neuro-adaptive controllers. In order to be able to have a basis for comparison, well-tuned PI and PID controllers are also designed for the same control loops. It is seen that the performance of the proposed intelligent control modules is by order of magnitude better compared to those obtained from the conventional controllers when used alone (calculated as the sum-squared tracking error). Another prominent feature that should be emphasized is the computational simplicity of the proposed approach.

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