Flight Demonstration of Adaptive Control System Using Neural Network

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Adaptive flight control systems can accommodate errors due to aerodynamic changes or control surface failures in mid-air. In this paper, a feedback error learning (FEL) approach employing a neural network is considered as an adaptive system. In FEL, the neural network is set parallel to the conventional feedback controller. Through online training, the neural network learns to minimize the conventional feedback controller’s output. The result is that it approximates the inverse dynamics of the aircraft and can thus work as a feedforward controller. Flight experiments were conducted with a small unmanned aerial vehicle. Two cases were considered as simulated failures: a trim setting error and a gain scheduling error. Experimental results demonstrated that the neural network can improve the control performance in case of changing aircraft dynamic characteristics, thereby validating the method proposed.

1. INTRODUCTION

UAVs have been getting more widely used for various tasks, such as getting aerial images for disaster damage tracking or environmental observation. To ease their use, autonomous flight control systems for UAVs have been developed. Most common aircraft flight control systems are based on a linear feedback control method, which provides the aircraft stability and reliability. However such a system has certain unfavorable points too:

- The feedback controller cannot maintain the controllability during aerodynamic changes or control surface malfunction.
- A gain scheduling method is complicated, because proper feedback gains with linear aircraft dynamics have to be chosen beforehand for every flight phase.

Adaptive flight control systems have been subject to research to increase resilience to problems that occur in the air. Recently, the implementation of a neural network in flight control has been proposed for manned aircraft [1]. The authors’ group is investigating the application of a neural network controller using a feedback error learning (FEL) algorithm [2] to a UAV. In FEL, the neural network is added to the conventional feedback controller and learns to approximate the inverse aircraft dynamics [3]. The control system has a simple structure since the neural network learning relies
solely on the conventional feedback controller output. This is a strong point, as it allows the network to adapt to any change of dynamics without external information on the nature or the extent of the failure. This simplicity is suitable for the limited computer resources of a small UAV.

Refs. 2 and 3 studied the application of the FEL neural network controller to waypoint navigation control of a small UAV by using numerical simulations. However, flight experiments for the proposed method had not been carried out. In this research, we conducted UAV experiments to validate the neural network system in real flight conditions. The UAV has three types of control surfaces: ailerons, elevator, and rudders, but to simplify the investigation, the neural network is applied only to the control process that tracks the reference bank angle command by changing the aileron angle. We conducted experiments for the following two cases as simulated failures:

- a trim setting error: an aileron trim angle has a deflection of ~3 degrees from the neutral angle
- a gain scheduling error: the feedback gains are 20% of the proper gains

We conducted experiments with and without the neural network and compared the control performance in order to validate the effectiveness of the proposed method.

This paper is organized as follows. Section 2 describes the control architectures where a linear neural network tuned by FEL is implemented for a bank angle control system used in waypoint navigation. Section 3 presents flight experiments in which the two simulated failures are considered with and without the neural network system for a small UAV. The conclusions are provided in Section 4.

2. CONSTRUCTION OF AN ADAPTIVE FLIGHT CONTROL SYSTEM

2.1 FEEDBACK ERROR LEARNING

In this study, the neural network is trained in a feedback error learning (FEL) setting. FEL was proposed by Gomi and Kawato\textsuperscript{4}) to obtain an inverse model of an unknown plant and was applied to robot control problems.

The plant is initially controlled by a feedback controller; however, the desired output $\chi$ cannot be obtained because of the delayed response. Moreover, the ideal feedback controller cannot be designed because the plant model and the actual plant will always have some difference in their properties. In FEL, a neural network is set parallel to a conventional feedback controller as shown in Fig. 1 and the neural network training is performed based on the feedback controller output $u_{fb}$. Through this process, the neural network learns the inverse dynamics of the plant and works as a feedback controller, so the plant can be controlled precisely without delay. As a result, the neural network contributes to the improvement of the whole control performance.

In FEL, the network weights $w$ are updated by minimizing the evaluation function

$$E = \frac{1}{2} u_{fb}^2$$

i.e. minimizing the energy of the feedback control signal $u_{fb}$, by the error back propagation method. The weight increments $\Delta w$ are decided from the feedback output $u_{fb}$.
the feedforward output \( u_{\phi} \) and the learning rate \( \epsilon \) as follows:

\[
\Delta w = -\epsilon \frac{\partial E}{\partial w} = -\epsilon \frac{\partial u_{\phi}}{\partial w} u_{\phi} = \epsilon \frac{\partial u_{\phi}}{\partial w} u_{\phi}
\]

(1)

The following relation is used in the last expression in Eq. (1):

\[
\frac{\partial u}{\partial w} = \frac{\partial u_{\phi}}{\partial w} + \frac{\partial u_{\theta}}{\partial w}
\]

\[
\text{suppose } u = u_{\phi} \text{ i.e. } \frac{\partial u}{\partial w} = \frac{\partial u_{\phi}}{\partial w} = 0
\]

\[
\therefore \frac{\partial u_{\phi}}{\partial w} = -\frac{\partial u_{\theta}}{\partial w}
\]

(2)

Here, \( u_{\phi} \) is the desired input. In Eq. (1), the learning rate \( \epsilon \) is an important parameter which greatly influences the neural network learning process.

In this study, FEL is applied to the aircraft attitude angle control. In particular, the controller which generates the aileron angle \( \delta_{\alpha} \) from the bank angle command \( \phi_{\theta} \) is considered. The conventional feedback controller’s output \( \delta_{\phi_{\theta}} \) is constructed with a linear feedback gain \( K_{\phi} \) as follows:

\[
\delta_{\phi_{\theta}} = K_{\phi} (\phi_{\theta} - \phi) \]

(3)

In FEL, the inputs of the neural network, the number of neurons, and the basis function of the neurons, are significant factors. For example, when a typical nonlinear model with a sigmoid function based three-layer neural network is applied to the aileron – bank angle controller, it is observed that the convergence of the weights and bias is not good. Therefore, a simpler neural network is used in this study. The transfer function from the aileron angle \( \delta_{\alpha} \) to the bank angle command \( \phi_{\theta} \) can be expressed as \(2^{3}\):

\[
\frac{\delta_{\alpha}}{\phi_{\theta}} = \frac{a_{1}s^{4} + a_{2}s^{3} + a_{3}s^{2} + a_{4}s + a_{5}}{b_{2}s^{2} + b_{1}s + b_{0}}
\]

(4)

where \( a_{i} \) (\( i = 0,1,2,3,4 \)) and \( b_{i} \) (\( i = 0,1,2 \)) are constant aerodynamic coefficients. Eq. (4) can be transformed into time domain form as follows:

\[
b_{2}\delta_{\alpha} + b_{1}\delta_{\alpha} + b_{0}\delta_{\alpha} = a_{2}\phi_{\theta}^{(1)} + a_{4}\phi_{\theta}^{(3)} + a_{3}\phi_{\theta}^{(2)} + a_{4}\phi_{\theta}^{(1)} + a_{5}\phi_{\theta}
\]

(5)

When the roll angle command is given, the aileron angle can be calculated by solving the differential equation (5). One solution of the differential equation (5) is expressed by (6). In this study, a single linear neuron is considered as the neural “network” (Fig. 2), and the neural network output \( \delta_{\phi_{\theta}} \) is described as:
\[ \delta_{eff} = \sum_{i=0}^{\hat{z}} w_i \hat{\phi}_i^{(i)} + b_u \]  

(6)

where \( \hat{\phi}_i^{(i)} \) is a normalized form of \( \phi_i^{(i)} \).

The weights \( w_i \) and bias \( b_u \) of the neural network are updated by minimizing the evaluation function:

\[ E = \frac{1}{2} \dot{u}_{ps}^2 + \frac{1}{2} \dot{\delta}_{ps}^2 = \frac{1}{2} K_p (\phi - \hat{\phi}_i)^2 \]  

(7)

With learning rate \( \varepsilon \), the weight increments \( \Delta w_i \) and the bias increment \( \Delta b_u \) for the current time step are computed by the equation:

\[ \Delta w_i = \varepsilon \delta_{ps} \hat{\phi}_i^{(i)} \quad (i = 0,1,2) \]

\[ \Delta b_u = \varepsilon \delta_{ps} \]

(8)

2.2 GUIDANCE SYSTEM

In this research, two guidance systems are used - waypoint tracking and line tracking (Fig. 3). In the waypoint tracking, the target is a given discrete point. The bank angle command \( \phi_i \) is linearized in respect to the sight line angle \( \Delta \eta_i \), which is the angle between the direction to the target and the ground velocity vector of the aircraft.

\[ \phi_i = K_i \Delta \eta_i \]  

(9)

In the line tracking guidance system, the target is given as a continuous line. The point \( \Delta h \) (in this research, \( \Delta h = 100 \text{ m} \)) in front of the foot of the perpendicular to the target line through the aircraft’s center of gravity, is considered as a waypoint. Of course this virtual waypoint is constantly updated. Similar to the waypoint tracking, the bank angle command \( \phi_i \) is linearized in respect to the angle between the direction to the virtual waypoint and the aircraft’s ground velocity vector.

\[ \phi_i = K_i \Delta \eta_i \]  

(10)

3. EXPERIMENT RESULTS

To demonstrate the capability of the FEL neural network control system, we conducted experiments with the small electric powered UAV shown in Fig. 4. The main dimensional data of this UAV are as follows: mass 1.950kg, wing area 0.392m², wing span 1.75m, mean aerodynamic chord 0.234m, aspect ratio 7.81. Since it is difficult to generate actual failure during flight, we conducted the experiments for two cases – a trim setting error and a gain scheduling error as simulated failures. In both cases the waypoints were on a rectangle of 150m by 300m. The guidance system used line
tracking on the 300m lines and waypoint tracking on the 150m parts, with the next corner point as waypoint. The commanded altitude was 80m and air speed was 15m/s. The weights of the neural network were updated at 16 Hz, and the learning rate $\epsilon$ was 0.05. Since the bank angle was oscillating due to the wind in the experiments, the learning rate $\epsilon$ was set to a smaller value than in the numerical simulation.

In the experiments, an autonomous flight system based on the conventional feedback controller was used in takeoff. Once a steady flight condition was reached, the simulated failures were introduced and the performance of the controller with and without the neural network was investigated. Finally, the failure simulation was terminated and the normal conventional feedback controller was used for landing. The command to start using the neural network and commands to start and stop simulating the failures could be sent from the ground station (mobile computer). The timing of using the neural network and simulating the failures could be changed in response to the wind or the position of the UAV.

3.1 TRIM SETTING ERROR

The first case is the aileron trim angle failure. The experiments were conducted with an aileron trim angle deflection of $-3$ degrees from the neutral angle. This simulated failure aimed to prove that the adaptive system can sustain the controllability even when the aircraft dynamics changes suddenly. Fig 5 shows the time histories of the bank angle, its command and the aileron angle while the neural network was working. The failure simulation started at 268.5s. The neural network output compensated for the aileron angle deflection and the bank angle followed the command even after the failure. Fig. 6 shows the time histories of the weights and the bias of the neural network. When the trim angle was 0 degrees, the average of the bias was $-0.5790$, when the trim angle deflection was $-3$ degrees, the average of the bias was $2.5897$. The bias works like an integral controller to compensate for the deflection of the trim angle.
Fig. 6  Weights and Bias of the Neural Network

Fig.7 shows the UAV bank angle and aileron angle when only the conventional feedback controller is used and Fig. 8 shows the trajectory of the UAV for both cases. Since the conventional controller did not include an integral controller, the bank angle had a deviation from the command value, and the trajectory did not follow the waypoints. On the other hand, when the neural network was active, the UAV was able to follow the waypoints and track the target lines.

Fig. 7  Bank Angle and Aileron Angle
without Neural Network

Fig. 8  Trajectory of the UAV
3.2 GAIN SCHEDULING ERROR

One of the disadvantages of feedback controllers is the difficulty of choosing feedback gains. The gain scheduling error experiment was conducted with 20% of the proper gain. Figs. 9 and 10 show the time histories of the bank angle, its command and the aileron angle during the gain scheduling error. When the neural network was active, the bank angle followed the command more closely than when the neural network was inactive. Fig. 11 shows the trajectory of the UAV with and without the neural network. When the neural network did not work, the UAV easily meandered, but when the neural network was working, the UAV caught the waypoints. We conclude that the neural network can make augmentation signals under the gain scheduling error.

Fig. 9   Bank Angle and Aileron Angle  
without Neural Network

Fig. 10   Bank Angle and Aileron Angle  
with Neural Network

Fig. 11   Trajectory of the UAV
4. CONCLUSIONS

In this research, the ability of a neural network as a bank axis controller was investigated, and experiments with a small UAV were conducted. The experiments included a trim setting error case and a gain scheduling error case. When the neural network system was active, the bank angle followed the command and the UAV was able to follow the waypoints under both errors. The experimental results proved that the system with the neural network compensated for errors in real flight conditions.

For the learning rate \( \varepsilon \) a smaller value was used than in a previous numerical simulation. For choosing the proper learning rate \( \varepsilon \), it should be adjusted in flight or a simulation which is more like the real flight condition should be developed.

It is necessary to carry out more experiments in order to identify the limit performance of the proposed method for more serious accidents or in stronger wind conditions. Additionally, real impairments of the airframe and actuator system should be investigated since the present experiments only considered simulated failures.

REFERENCES


