FAULT TOLERANT CONTROL SYSTEM OF AIRCRAFT BY FEEDBACK ERROR LEARNING WITH SYSTEM ESTIMATION

Nobuyuki Yoshikawa*
*Department aeronautics and Astronautics, the University of Tokyo, Tokyo, Japan

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Abstract

In this paper, the fault tolerant control system of aircraft by feedback error learning with online model estimation is investigated. Conventional feedback error learning method takes time to re-acquiring the inverse model and control would be unstable during the re-learning. To avoid this problem the online model estimation based on linear regression was introduce. Using model information, required parameter change and learning time of the controller is reduced. To evaluate the stability and followability of pitch control of the boeing 747, the computer simulation of the longitudinal motion was performed with 2 fault cases, the elevator gain reduction and the longitudinal static stability loss.

1 Introduction

In recent years, the air transportation demand has been increasing by 5% per year [14], with a presuming high increasing ratio because of globalization and a growth of developing countries. At the same time, the number of flight increases, with a increase of the number of accident. Thanks to a large investment in aircraft technology, the accidents caused by technical factors have been greatly suppressed and the accident rate has been decreased. However, the accident caused by human factor are left to be detected and controlled to reduce at best the overall ratio of accidents. In order to minimize the human factor in accidents, current civil aircraft are operated with multiple pilot to ensure their safety, hence pilots monitors each others, and work as a backup in case of pilot incapacitation.

Consequently a pilot manipulation assist system is required to make aircraft more safe and to solve the pilot shortage problem even if any fault happens. These systems rely on complex controllers that adapt the input command given by pilot in order to ensure the safety and dynamic of the aircraft. Several approaches has been proposed (see [10, 6], among several others, for a survey on aircraft control systems) to improve the efficiency of aircraft controls. A possible approach comes from the control systems and artificial intelligence communities, with the use of fuzzy systems or neural networks that aim at learning the optimal adaptation function of the controller with respect to input command [16, 9, 11, 6, 1, 13, 12, 2]. Neural networks has been empirically demonstrated to show good performances to replace different PID controller, as they are able to approximate non-linear and very complex functions. The aircraft controller is required high reliability. However the neural network is too complicated to understand the inner state for human. Moreover there are problem that the multiple layer neural network takes the long learning time and its control signal is not optimal during learning.

Therefore The fault tolerant control system of aircraft fault by feedback error learning with online model estimation (MeFEL) is investigated in this paper. FEL is an adaptive control method proposed by Kawato's team. The system estimation of the control target aircraft is performed and the estimated parameters are used as the input of the MeFEL controller according to the aircraft model formula. So in this proposed method, the single perceptron can be used as the adaptive controller and it is simple and easy to understand for human operator. MeFEL is divided into 2 blocks, a linear regression-based system estimator and a neural adaptive controller using estimated parameters. In this paper, MeFEL fault tolerant control stability and readiness were evaluated by the simulations with two fault model, the elevator gain reduction and the longitudinal static stability loss. MeFEL shows that it is superior in terms of stability and readiness.

2 Background

2.1 Aircraft Modeling

In this paper, aircraft pitch angle is a control target. Aircraft longitudinal motion is described by 2 parts, the elevator dynamics and the aircraft body dynamics. The elevator dynamics can be written as Eq.1, and the aircraft body dynamics can be written as Eq.2, respectively.

$$\dot{\delta}_e = \tau\left[K\delta_{ec} - \delta_e\right] \tag{1}$$

$$\dot{\boldsymbol{x}} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\delta_e \tag{2}$$

where δ_e is an elevator angle deflection, δ_{ec} is an elevator angle command, τ is a time constant of elevator, K is a elevator gain, $\boldsymbol{x} = \left[\, u \;\; v \;\; q \;\; \theta \,\right]^{\mathrm{T}}$ is a state vector, and $\boldsymbol{A}$, $\boldsymbol{B}$ are the state-space matrices, respectively.

2.2 Feedback Error Learning

Feedback Error Learning (FEL) is proposed by Dr. Kawato, which is mimicking the learning mechanism of the motor nerves system in the human cerebellum [7]. Ordinarily, a neural controller is attached in parallel to the feedback controller. The weight parameters of FEL neural controller are trained with the stochastic gradient descent by using the feedback control signal as teacher signal. Using a feedback error as an input of the FEL neural controller, the FEL neural controller learns as a kind of regulator [5], which equations are described as the followings:

$$\begin{aligned}
u_b &= K_p\xi + K_i\int\xi dt + & (3)\\
u_n &= f(\ddot{\theta}_d, \dot{\theta}_d, \theta_d, \dot{\theta}, \theta, W_c) & (4)\\
u &= u_b + u_n & (5)\\
J_C &= \frac{1}{2}u_b^2 & (6)\\
\dot{\pi} &= -\eta\nabla_W J_C & (7)
\end{aligned}$$

where θ and θ_d is the pitch angle deflection and its command, $\xi = \theta_d - \theta$ is a residual error, $f(\cdot)$ is a neural network, W is a weight parameter, J_c is a cost function, η is a learning rate, ∇_W is a gradient operator for each weight.

2.3 Adam

Adam is an one of stochastic gradient descent method which is well known at machine learning community [8]. Adam has been proposed based on the momentum SGD, and method which has auto-tuned learning rate like AdaGrad [3], RMSProp [15].

$$\begin{aligned}
m &= \beta_1 m + (1-\beta_1)\nabla J & (8)\\
v &= \beta_2 v + (1-\beta_2)\nabla J^2 & (9)\\
\hat{m} &= \frac{m}{1-\beta_1^T} & (10)\\
\hat{v} &= \frac{v}{1-\beta_2^T} & (11)\\
\Delta\boldsymbol{W} &= -\alpha\frac{\hat{m}}{\sqrt{\hat{v}}+\varepsilon} & (12)
\end{aligned}$$

Originally T indicates the number of learning step, however in this study $T = t + 1$ second is used, t is a simulation time. $1 - \beta^T$ should be almost 1 in the normal flight.

3 Model Estimation Feedback Error Learning

The FEL neural controller takes a time to reacquire the inverse model of control target after change of system by occurring fault. During relearning, the control of FEL can not be said stable. Therefore, we tried to reduce learning time and keep stability during learning by using the real-time estimated parameters of the control target as input information.

3.1 Real-time Model Estimation

Many parameter estimation are proposed in various communities [4]. The linear regression-based online SGD method is adapted in MeFEL.

To control the aircraft longitudinal attitude, the long term mode, like Phugoid mode, affects a little. Therefore only short term mode is considered and it is known that it can be modeled as second order lag system as bellow:

$$\ddot{\theta} = -M_q\dot{\theta} - M_w\theta + M_{\delta_e}\delta_e \tag{13}$$

So the linear regression model for θ can be considered with an input vector consisted with $\ddot{\theta}$, $\dot{\theta}$ and δ_e as the followings:

$$\begin{aligned}\dot{\theta}_p &= \boldsymbol{W}_e{}^{\mathrm{T}}\boldsymbol{x}_e & (14)\\ J_e &= \frac{1}{2}\left(\dot{\theta}_p - \dot{\theta}\right)^2 & (15)\\ \Delta\boldsymbol{W}_e &= Adam(\nabla_{W_e}J_e) & (16)\end{aligned}$$

where $\boldsymbol{x}_e = \left[\dot{\theta}\ \theta\ \delta_e\right]^{\mathrm{T}}$ is an input vector, $\boldsymbol{W}_e = \left[W_{e1}\ W_{e2}\ W_{e3}\right]^{\mathrm{T}}$ is a parameters to be estimated as the system parameters of the aircraft short term dynamics as $\boldsymbol{W}_e \to \left[-M_q\ \ -M_w\ \ M_{\delta_e}\right]^{\mathrm{T}}$.

3.2 MeFEL construction

In previous research, the input vector of FEL neural controller is constructed by derivatives of the pitch command up to second order as $\boldsymbol{x}_{fel} = \left[\ddot{\theta}\ \dot{\theta}\ \theta\right]^{\mathrm{T}}$ with regarding the aircraft as second order lag system. The conventional FEL network takes time to find optimal parameters to be the inverse model. The inverse model is described by transforming Eq.(13) as below:

$$\delta_e = \frac{1}{M_{\delta_e}}\ddot{\theta} + \frac{M_q}{M_{\delta_e}}\dot{\theta} + \frac{M_w}{M_{\delta_e}}\theta \tag{17}$$

Therefore considering these coefficients, estimated parameters are used for the input vector of MeFEL Fig.(1). The input vector of MeFEL is constructed as below:

$$\boldsymbol{x}_c = \left[\frac{1}{M_{\delta_e}}\ \ \frac{M_q}{M_{\delta_e}}\ \ \frac{M_w}{M_{\delta_e}}\right]^{\mathrm{T}} \odot \boldsymbol{x}_{fel} \tag{18}$$

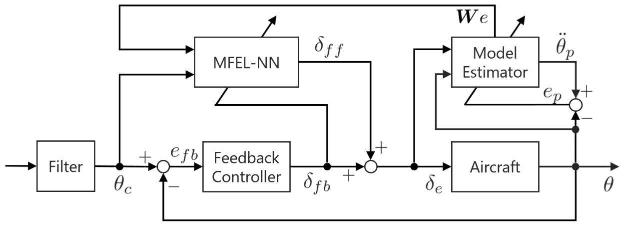

Fig. 1 MeFEL block diagram

where $\odot$ indicates Hadamar product. Using this input vector, the controller network output is written as below:

$$u_{nn} = \boldsymbol{W}_c^{\mathrm{T}}\boldsymbol{x}_c \tag{19}$$

Therefore the elevator command is:

$$\delta_{ec} = u_{nn} + u_{fb} \tag{20}$$

4 Simulation

In this paper, the computer simulation was performed to evaluate the ability of MeFEL.

4.1 Experimental Settings

As a control target aircraft, the linear longitudinal model of Boeing 747 was used. The elevator time constant was $\tau = 1/37$, and the elevator gain was $K = 1$. The state-space matrices were described as the followings:

$$\boldsymbol{A} = \begin{bmatrix} 0 & 4.8585 & -32.1434 & 0 \\ -0.1085 & -105.8 & -1.3802 & 651.3479 \\ 0 & 0 & 0 & 1 \\ 0.00004 & -0.3895 & 0.00002 & -0.6439 \end{bmatrix}$$

$$\boldsymbol{B} = \begin{bmatrix} 0 \\ -25.1185 \\ 0 \\ -1.6895 \end{bmatrix}$$

Adam parameters has the recommended values proposed in the original paper [8]. According to this recommended values, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\varepsilon = 10^{-8}$ were used. In other hand, the adaptive speed $\alpha = 0.1$ was used as the MeFEL original value.

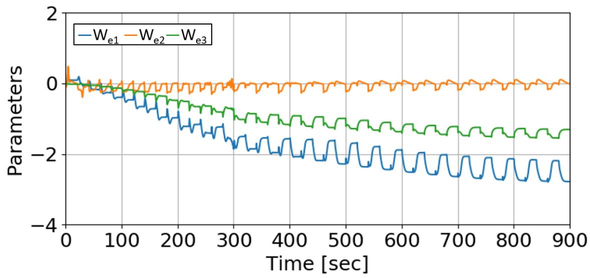

Fig. 2 Model parameter estimation

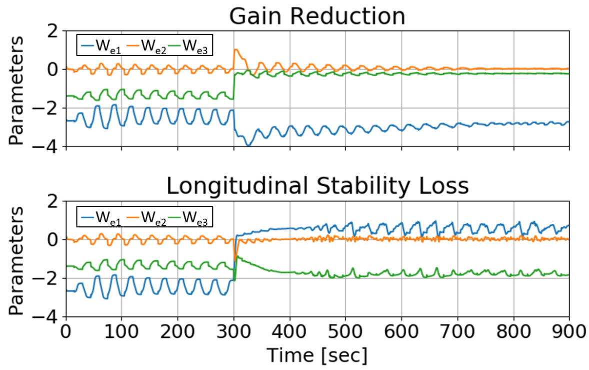

Fig. 3 Model parameter estimation on fault occurrence

4.2 Estimation

4.2.1 Initial Estimation

To find an initial values for the state estimator, a simulation of the parameter estimation with normal state aircraft model was performed Fig.(2). As an initial condition, the zero vector was used as the state estimator parameters as $W_e = \mathbf{0} \in \mathbb{R}^3$. Pitch angle command was a rectangle wave with an amplitude $A_\theta = \pm 2$ deg., a period $T_\theta = 30$ sec., through a second order low path filter as:

$$F(s) = \frac{1}{(0.5s+1)^2} \tag{21}$$

4.2.2 Fault Detection

The elevator gain reduction and the longitudinal stability loss were assumed as the fault model. The 80% reduction of elevator effectiveness is assumed as the elevator gain reduction as $M_{\delta_e} = -1.6895 \rightarrow -0.3379$. The stability derivative $M_w = -0.3895 \rightarrow 0.19475$ is assumed as the longitudinal stability loss. Both fault were occurred

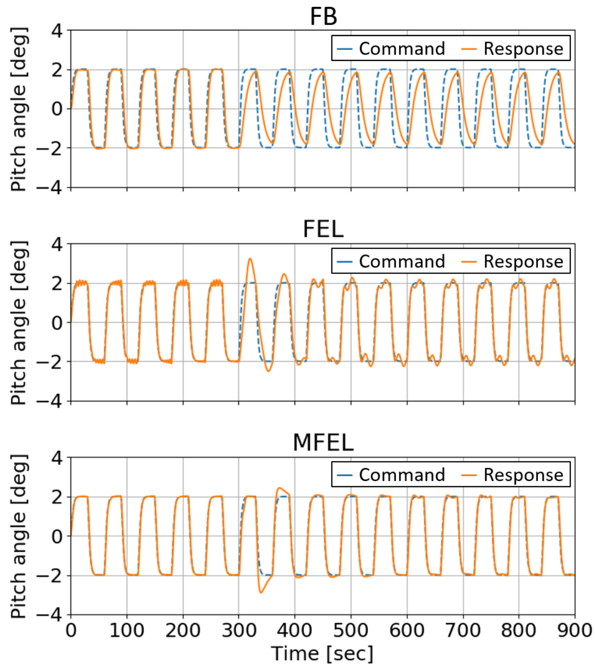

Fig. 4 Pitch angle response on the fault of the elevator gain reduction

at $t = 300$ sec. The initial parameters of the model estimator was $\boldsymbol{W}_e^0 = [\,-1.307 \;\; -2.784 \;\; -0.01756\,]^{\mathrm{T}}$. Fig.(3) shows the result of fault detection by the model estimator. The upper panel and lower panel show the estimated parameters on the elevator gain reduction and the longitudinal static stability loss, respectively.

4.3 Fault Tolerant Control

4.3.1 Elevator gain reduction

Occurrence of reducing elevator efficient in flight was assumed. Pitch angle command period was $T_\theta = 60$ sec. was used. Initial estimator weight parameters were same to section 4.2.2, and other conditions were 4.1 and 4.2.

Simulation results of pitch angle control response by the state feedback, the conventional FEL, and MeFEL are shown in Fig.(4). The followability by the conventional FEL had been deteriorated immediately after fault happened. Following learning progresses of controller, followabolity had recovered however vibration was seen even at t = 900 seconds. MeFEL followa-

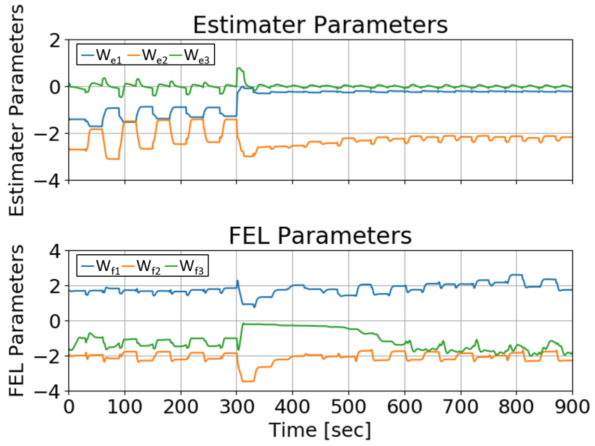

Fig. 5 The estimator and controller parameters change on the fault of the elevator gain reduction

bility also had been decrease, however it had recovered after 100 seconds. Fig.(5) shows the weight parameter changes, upper and lower panel indicate the system estimator and the MeFEL neural controller, respectively. After fault happened both of the estimater and MeFEL controller weight parameters were changed. After learning,the parameter W_{e3} corresponding to the elevator gain M_{δ_e} was reduced 80.0% as $W_{e3} = -1.037 \rightarrow -0.208$. The MeFEL parameters were temporally varied soon after fault happened, and they were finally converged to $0.99 \sim 1.15$ times initial values.

4.3.2 Longitudinal stability loss

The loss of the longitudinal static stability in change in the center of gravity was assumed. Fault characteristic was same to section 4.2.2, and other condition were same to section 4.3.1.

Fig.(**??**) shows the pitch angle responses by state feedback, conventional FEL, and MeFEL. There was not any divergence nor large reduction of followability in all control method. The vibrations were observed in all method. However the amplitude of vibration with MeFEL was smaller than other methods. The estimator and MeFEL weight parameter changes are shown in Fig. (7). The weight parameter W_{e2} corresponding to M_w was changed -0.26 times as $W_{e2} = -2.783 \rightarrow$

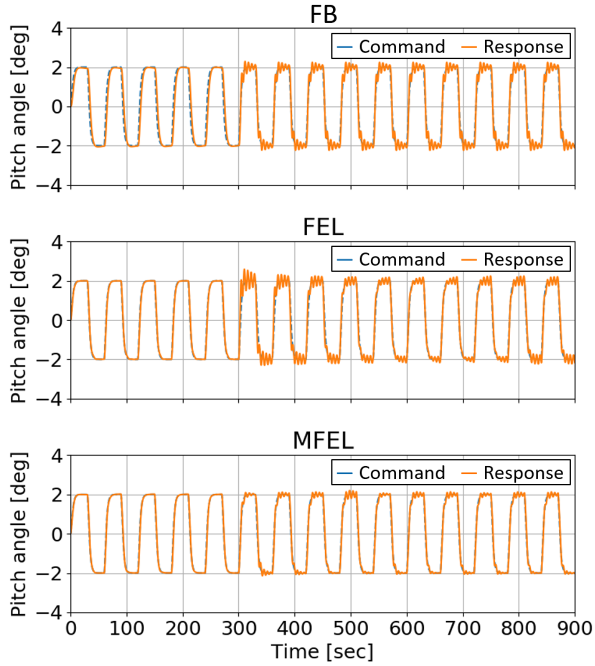

Fig. 6 Pitch angle response on the fault of the longitudinal static stability loss

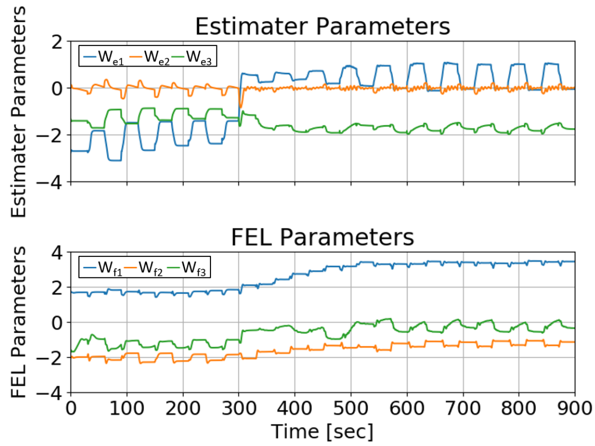

Fig. 7 The estimator and controller parameters change the fault of the longitudinal static stability loss

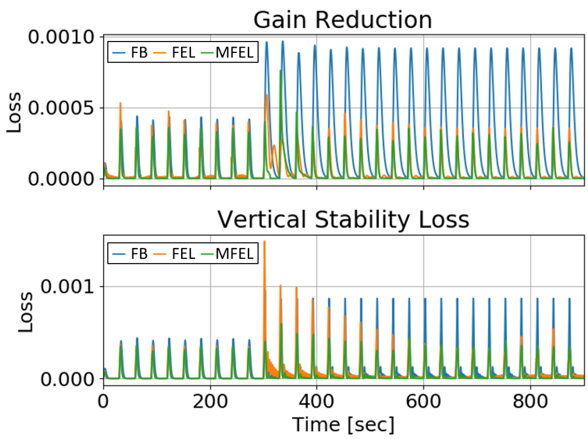

Fig. 8 Loss function of the fault tolerant control, gain reduction and stability loss by PID, FEL, and MeFEL

0.726, and W_e3 was changed to 1.4 times initial value.

5 Discussion and Conclusion

To evaluate the control stability between each method, the loss function consisted with square sum of the residual error of pitch angle and pitch angle velocity was defined as below:

$$J = \frac{1}{2}\left[(\theta_c - \theta) + q^2\right] \tag{22}$$

The losses for each method are shown in Fig.(8). In both fault occurrence, the losses of MeFEL was smaller than conventional FEL control expected soon after fault happened. In conventional FEL scheme, the FEL network has to learn and re-acquire the inverse model by changing controller weight parameters to adapt the system change due to fault. A large learning rate is generally used to improve learning speed, however it leads the parameter oscillation in normal state flight, and the too large over shoot during re-acquiring the inverse model. These parameter variations make the control unstable. In other hand, MeFEL scheme can use small adaptive rate for both of neural controller and the model estimator. Because the model estimator's learning rate is slightly large than the controller, the estimator can learn the system change faster than controller. It requires small parameter change in the neural controller, and it can be said that improves the control stability when the fault happens.

In this paper, the model estimation-based feedback error learning (MeFEL) was investigated, and evaluated its fault tolerant control stability of aircraft longitudinal motion. MeFEL was improved the stability better than conventional FEL by using online model estimation based on linear regression and introducing the Adam method.

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6 Contact Author Email Address

To make any contact, send an e-mail to nyoshikawa@g.ecc.u-tokyo.ac.jp or yoshikawa.ut@gmail.com.

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