SEVERAL NEW APPROACHES FOR FAULT TOLERANT FLIGHT CONTROL SYSTEM

Youdan Kim*, Seungkeun Kim*, Chaeik Ahn*
***Seoul National University, Korea**

Keywords: *fault tolerant control, fault diagnosis, multiple model, IMM filter, adaptive control*

Abstract

Aircraft actuator or sensor failure may cause serious problems, and therefore aircraft control system must have the capability to reconfigure its own structure or control gains against a failure. Recently, several approaches for fault tolerant control system design have been proposed. These approaches are divided into two categories: fault-detection-and-diagnosis-based approach and adaptive-control-based approach without fault detection and diagnosis process. In this study, several fault tolerant techniques are proposed and compared with each other. For a fault-detection-and-diagnosis-based approach, a mode switching technique using fuzzy-tuning interacting multiple model filter is presented. In addition, the direct adaptive control method is considered for an adaptive-control-based approach. Finally, adaptive control system using multiple model mode switching is also considered. To validate and compare the proposed fault tolerant control systems, numerical simulations are performed for the high performance aircraft with the control surface failure.

1 Introduction

The primary purpose of fault tolerant control system design is to achieve higher reliability even when control surface or sensor failures occur during the flight. To this end, the control system must have the capability to redesign its own structure or to recompute control gains in the event of a failure. Currently, there are two approaches to design the fault tolerant control system. First one is the fault-detection-and-diagnosis-based approach. In this approach, an efficient and accurate fault detection and diagnosis algorithm is required. Second approach is the adaptive-control-based approach without the fault detection and diagnosis process. Eliminating the fault detection and diagnosis process makes the fault tolerant control system algorithm simple and allows it to adapt quickly to unknown faults.

In this study, several fault tolerant flight control approaches are considered and compared with each other. For the fault-detection-and-diagnosis-based approach, a mode switching technique using fuzzy-tuning interacting multiple model filter (FIMM) [1] is presented to improve the performance of the existing interacting multiple model filter. In addition, model-following direct adaptive control (MDAC) method [2-3] is considered, which employs the model following control scheme. This method does not need the persistent input excitation condition and parameter identification process. Finally, multiple model adaptive control (MMAC) [4] is proposed to compensate the drawback of simple adaptive control. To validate and compare the proposed fault tolerant control systems, numerical simulations are performed for the high performance aircraft with the control surface failure.

This paper is outlined as follows: Section II describes fault tolerant control techniques. Section III shows numerical simulations to compare the performance of each approach. Finally, Sec. VI presents the conclusions.

2 Fault Tolerant Control Techniques

2.1 Mode Switching Based on Fuzzy-tuning IMM Filter

The algorithm of the IMM filter is a recursive algorithm composed of the following four steps: interaction/mixing, filtering, model probability update, and estimate combination as shown in Fig. 1. The input to the filter matching to a certain mode is obtained by mixing the state estimates of all filters at the previous step under the assumption that this particular mode is in effect at the present step. Then, a conventional Kalman filtering is performed in parallel. The model probabilities are updated based on the model-conditional likelihood functions. Finally, the overall states are estimated from the probabilistically weighted sum of outputs from each filter. The detailed process of conventional IMM filter can be found in [5].

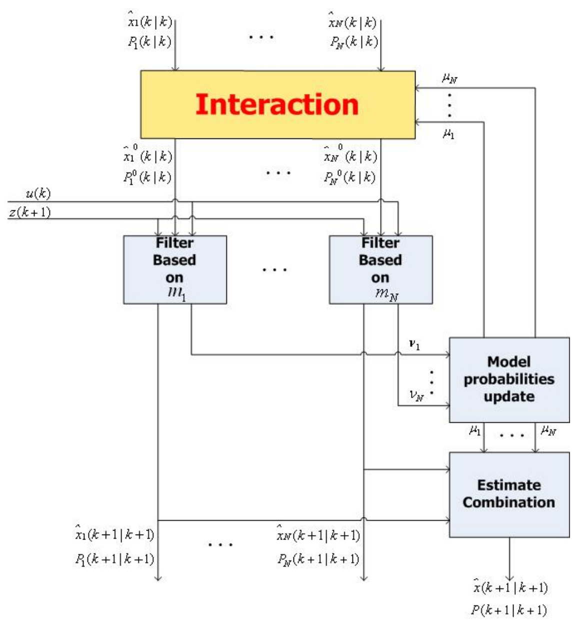


Fig. 1. Structure of the IMM filter

Model probabilities can indicate the effect of each mode to the system at the present step. Therefore, Fault Detection and Diagnosis (FDD) can be achieved utilizing the model probabilities. The fault decision can be accomplished by comparing the ratio between the maximum and the second maximum model probability.

In IMM filter, the transition probability plays an important role to interact and mix the information of each individual filter. However, an assumption that the transition probability is constant over the total period of FDD can cause some troubles. Even if the Fault Tolerant Control (FTC) treats with the first failure successfully, the unchanged transition probability can mislead the FDD to intermittently declare the false failure. This comes from the fact that the normal mode before the first failure is not the normal case any longer. On that account, the fuzzy-tuning algorithm of the transition probability is proposed in [1].

The transition probability from any particular mode to the normal mode is generally set larger than others in order to prevent a false fault diagnosis. However, it may have a bad influence on performing correct fault diagnosis when fault occurs. This weakness can be overcome by adjusting the transition probability after the occurrence of the fault. For example, if the model probability of a certain failure mode has larger than that of any other mode for an assigned time, then the transition probability related to the corresponding mode should be increased to reflect the current model condition.

Fuzzy-tuning algorithm is proposed to adjust the transition probabilities effectively. In this study, a determination variable C_i is introduced. This variable decides whether or not the transition probabilities are adjusted. The increment of the determinant variable can be obtained through the fuzzy logic with inputs composed of model probabilities at every step. The initial value of each mode's determination variable is set to be zero. Once the determination variable C_i of certain mode exceeds the pre-defined threshold value, then the transition probabilities from every mode to that mode are increased. Finally, the determination value of each mode is initialized. This process is illustrated in Fig. 2.

Fuzzy inference system is designed using TSK (Takagi-Sugeno-Kang) model [6]. Once the count variable of a certain fault mode exceeds the threshold value, then all the elements of the transition matrix from the other modes to the corresponding fault mode are increased. The transition probability is changed only when one fault mode is dominant for a while more than the pre-defined confirmation time. For the confirmation time, 0.5 second is chosen. By this process, the proposed tuning scheme of transition probabilities based on fuzzy logic can make FDD using IMM filter more efficient and reliable.

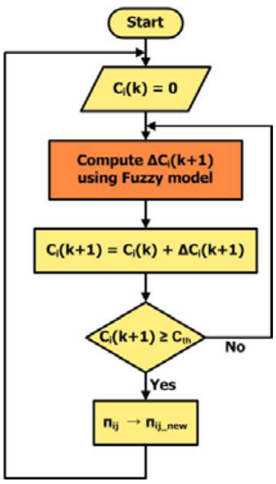


Fig. 2. The flowchart of fuzzy-tuning algorithm

The discrete-time command generator tracker was derived for the feedback controller of each failure mode [1]. In this study, the following strategy is adopted for reconfigurable control law: (i) each command tracker is designed based on the model matching to a particular fault mode. (ii) when the fault mode *i* is declared, then the controller is switched to the corresponding *i*th mode's command tracker. The reconfiguration process is shown in Fig. 3.

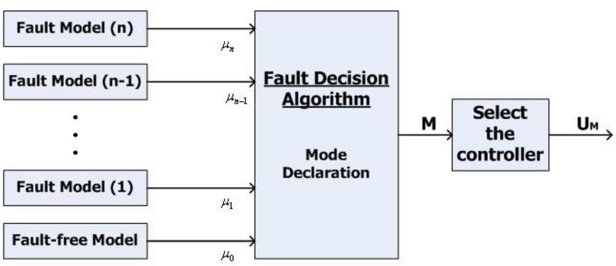


Fig. 3. Fault tolerant control strategy using mode switching

2.2 Model-following Direct Adaptive Control

In this section, a new adaptive controller based on the model following control scheme is proposed. Linearized system dynamics for a given flight condition can be represented as

$$\dot{x} = Ax + Bu + d \tag{1}$$

$$y = Cx \tag{2}$$

where $d \equiv -Ax_0 - Bu_0$ is included to maintain the trim condition, and subscript zeros denote trim values. The reference model is chosen as follows.

$$\dot{y}_m = A_m y_m + B_m r \tag{3}$$

where r is the reference input, A_m is a stable system matrix, and B_m is an invertible input matrix. The objective of the model following controller is to make the system output y follow the reference model output y_m. For the system and model represented by Eqs. (1)-(2), and (3), the following controller was proposed for the reconfigurable flight control system [7].

$$u = C_0 r + G_0 x + v \tag{4}$$

where matrices C_0, G_0 are adaptive control gain matrices, and v is an adaptive control vector. However, to derive the gradient-based adaptive rules from the above controller structure, Eq. (4) causes a so-called bilinear problem which is a multiplication of parameterized matrices. Because the bilinear problem makes the constructing of adaptive rules difficult, the following modified controller is proposed to derive gradient-based adaptive controller [2-3].

$$u = C_0 r + C_0 G_0 x + C_0 v + C_0 L_0 e \tag{5}$$

where K_0 is a constant gain matrix. Besides the bilinear problem, the main difference between Eq. (4) and Eq. (5) is the existence of $C_0 L_0 e$. By adding this term to the controller, a more robust controller can be obtained.
Using Eqs. (1)-(2), (3), and (5), the output error dynamics can be expressed as follows:

$$\begin{aligned}\dot{e} &= \dot{y} - \dot{y}_m \\ &= (CA + CBC_0G_0)x + CBC_0 r + CBC_0 v \\ &\quad + CBC_0 L_0 e + Cd - A_m y_m - B_m r\end{aligned} \tag{6}$$

To guarantee the asymptotic convergence of the output error e, the following relations should be satisfied.

$$CA + CBC_0^* G_0^* = A_e C \tag{7}$$
$$CBC_0^* = B_m \tag{8}$$
$$CBC_0^* v^* = -Cd \tag{9}$$
$$CBC_0^* L_0^* = \sigma A_m, \ \sigma > 0 \tag{10}$$

where superscript asterisk denotes an unknown true value or nominal value. The gain matrix L_0 can be obtained by Eq. (8) and (10) as

$$L_0 = L_0^* = \sigma B_m^{-1} A_m \tag{11}$$

Substituting Eqs. (7)-(8) into Eq. (6) and using Eqs. (8) and (11), we have

$$\begin{aligned}\dot{e} &= (1+\sigma)A_m e + CBC_0^*(G_0 - G_0^*)x \\ &\quad + CB(C_0 - C_0^*)(G_0 x + r + v + L_0 e) \\ &\quad + CBC_0^*(v - v^*)\end{aligned} \tag{12}$$

Let us define the following error matrices and error vector.

$$\vartriangle G = G_0 - G_0^* \tag{13}$$
$$\vartriangle \psi = C_0^{*-1} - C_0^{-1} \tag{14}$$
$$\vartriangle v = v_0 - v_0^* \tag{15}$$

Substitution of Eqs. (5), (8), and (13)-(15) into Eq. (12) yields the desired error dynamics.

$$\dot{e} = (1+\sigma)A_m e + B_m \vartriangle G x + B_m \vartriangle \psi \, u + B_m \vartriangle v \tag{16}$$

Update rules for adaptive gains can be derived considering the following Lyapunov candidate function.

$$V = e^T P e + tr\left[\frac{\vartriangle G^T \vartriangle G}{\gamma_1}\right] + tr\left[\frac{\vartriangle \psi^T \vartriangle \psi}{\gamma_2}\right] + \frac{\vartriangle v^T \vartriangle v}{\gamma_3} \tag{17}$$

where matrix P satisfies the following equation.

$$A_m^T P + PA_m = -Q, \quad Q > 0 \tag{18}$$

Differentiating Eq. (17) with respect to time and using Eq. (16), we have

$$\begin{aligned}V &= (1+\sigma)e^T(PA_e + A_e P)e \\ &\quad + 2e^T P(B_m \vartriangle G x + B_m \vartriangle \psi u + B_m \vartriangle v) \\ &\quad + 2tr\left[\frac{\vartriangle G^T \vartriangle \dot{G}}{\gamma_1}\right] + 2tr\left[\frac{\vartriangle \psi^T \vartriangle \dot{\psi}}{\gamma_2}\right] + 2\frac{\vartriangle v^T \vartriangle \dot{v}}{\gamma_3}\end{aligned} \tag{19}$$

Using Eq. (18) in Eq. (19), we have

$$\begin{aligned}\dot{V} &= -(1+\sigma)e^T Q e + 2tr[\frac{1}{\gamma_1}\vartriangle G^T(\vartriangle \dot{G} + \gamma_1 B_m^T P e x^T) \\ &\quad + \frac{1}{\gamma_2}\vartriangle \psi^T(\vartriangle \dot{\psi} + \gamma_2 B_m^T P e u^T)] \\ &\quad + \frac{2}{\gamma_3}\vartriangle v^T(\vartriangle \dot{v} + \gamma_3 B_m^T P e)\end{aligned} \tag{20}$$

The adaptive update rules for the negative definition of $\dot{V}$ can be obtained as follows under the assumption of constant *A*, *B*, and *d*.

$$\dot{G}_0 = -\gamma_1 B_m^T P e x^T \tag{21}$$
$$\dot{C}_0 = -\gamma_2 C_0 B_m^T P e u^T C_0 \tag{22}$$
$$\dot{v} = -\gamma_3 B_m^T P e \tag{23}$$

The non-positiveness of $\dot{V}$ is proved by substituting Eqs. (21)-(23) into Eq. (20) as

$$\dot{V} = -e^T Q e \le 0 \tag{24}$$

The above adaptive update rules do not require information about system parameters. This property is a good feature of the direct adaptive method.

2.3 Multiple Model Adaptive Control

Even though the system output tracking could be achieved by the model reference adaptive control (MRAC) scheme [8], the performance in the transient response at the beginning of the operation or after an abrupt change such as control surface damage, actuator/sensor failures may not be satisfactory. Thereafter, the typical adaptive controller cannot generate a proper control input that makes the system follow the reference model. To overcome the shortcomings in the transient response, multiple-model approach for parameter estimation has been proposed. This method can guarantee the stability of the overall system [9].

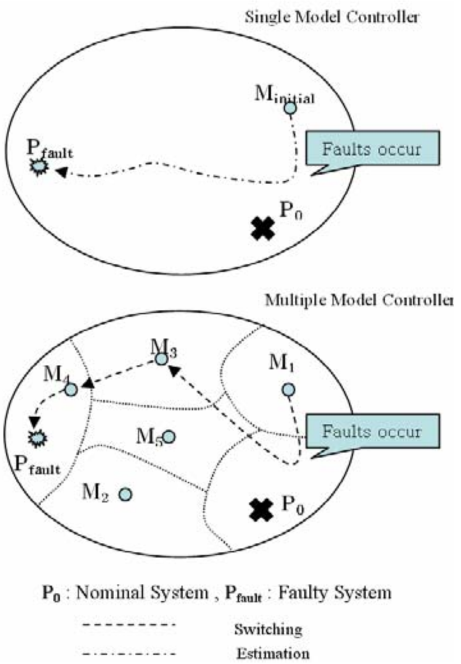


Fig. 4. Single model and multiple model

The multiple models, switching, and tuning (MMST) technique is based on the concept of describing the dynamics of the system using different models according to the wide range of operating conditions. Fixed models can be selected by referring to as the current system model or the various system models under the different conditions. Figure 4 shows the overall control system structures of the single model and the multiple models adaptive control scheme according to the parameter estimation.

The basic idea is to use the on-line estimates of the aircraft parameters to decide which controller to be chosen in a particular flight condition. Let us assume that the system dynamics are abruptly changed from the nominal system P_0 to the faulty system P_{fault} in the parametric set. The parametric set consists of the corresponding system model subsets; $M_1, \ldots, M_5$. When faults occur, the switching logic compares the output of the real system with the outputs of fixed models and selects a controller which minimizes the error between the real system and the fixed models. MRAC generates a proper control input with previous input and output information.

When a switching model is applied, the selected model initializes the reinitialized adaptive model, and this free-running adaptive model is operating in parallel with fixed models. This approach can improve the performance of controller. Figure 5 shows the concept of re-initialization procedure. If a selected model is a certain fixed model, re-initialized model is initialized by the parameters of the selected fixed model.

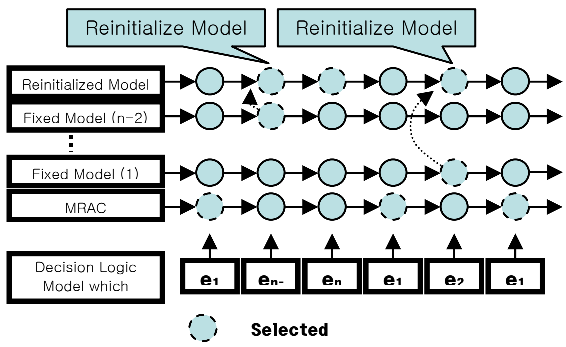


Fig. 5. Concept of re-initialization procedure

Output errors are generated by comparing the estimated system with the adaptive model, fixed models, and re-initialized model. The model which has a minimum error norm will be chosen to compute the control input. However, the mode switching may disturb the system because of the difference of dynamics between switching models. To deal with this problem, a modified adaptive model error is proposed using the following multiple models.

$$u(k) = (1-K)u_1(k) + Ku_{\min}(k) \tag{25}$$

where K is a switching input ratio. Furthermore, when the adaptive model error norm $|e_1(k)|$ is larger than a switching threshold value $e_{\text{threshold}}$, the switching model is selected to compensate the adaptive controller. This concept makes the system more stable by reducing the evitable and unnecessary transient change.

$$\begin{aligned} &if \quad e_1 > e_{\text{threshold}}, \quad then \\ &\quad e_1(k) = y(k) - \hat{y}_1(k) \\ &\quad \vdots \\ &\quad e_N(k) = y(k) - \hat{y}_N(k) \\ &u = u_{\min} \quad \text{at} \quad e_{\min} \end{aligned} \tag{26}$$

The total controller structure of MMAC is shown in Fig. 6.

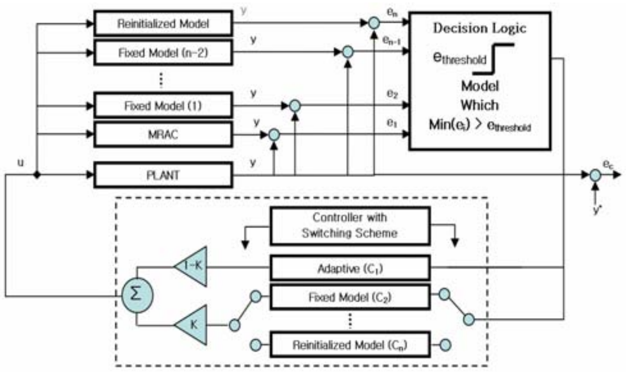


Fig. 6. Controller structure of MMAC

3 Numerical Simulations

In this study, the effectiveness of the proposed approaches is demonstrated using F-16 lateral dynamics flying at sea level with 700 ft/s [4]. The state variables are the sideslip angle β, roll angle ϕ, roll rate p, and yaw rate r. The control variables are aileron deflection δ_a and rudder deflection δ_r. The actuator failure model is adopted from [10]. One nominal model and fifteen failure models are considered for FIMM and MMAC as summarized in Table I.

Reference commands of sideslip angle and roll angle are chosen as

$$\begin{bmatrix} \beta_c \\ \phi_c \end{bmatrix} = \begin{Bmatrix} [0^\circ \;\; 0^\circ]^T & , \; 0 \le t < 5 \\ [2^\circ \;\; 10^\circ]^T & , \; t \ge 5 \end{Bmatrix}$$

To provide a smooth command, it is assumed that reference command is transferred to the controller through the following command filter.

$$H(s) = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2}$$

where $\omega_n = 3\; rad/s$, and $\zeta = 1$.

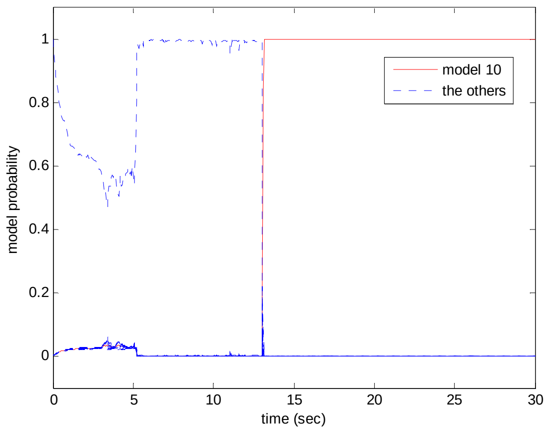
Table I. Multiple models in IMM filter

Model No.	Damage magnitude (%)		Model No.	Damage magnitude (%)	
	Rudder	Aileron		Rudder	Aileron
1	0	0	9	50	0
2	0	25	10	50	25
3	0	50	11	50	50
4	0	75	12	50	75
5	25	0	13	75	0
6	25	25	14	75	25
7	25	50	15	75	50
8	25	75	16	75	75

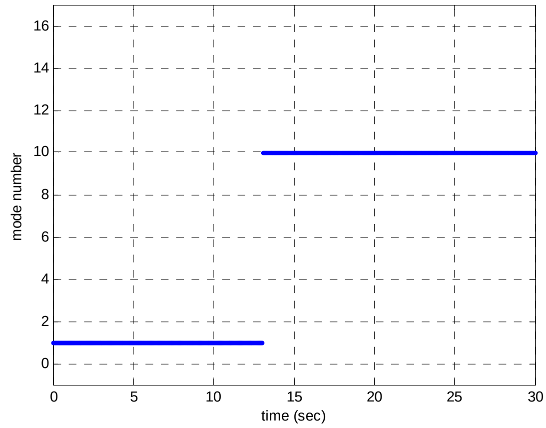
The process noise and the measurement noise are also considered in FIMM; Gaussian noises with zero mean values and variances $\sigma^2 = 0.001^2$ and 0.005^2, respectively. It is supposed that the failure with 49 % loss of the rudder and 27 % loss of the aileron occurs at 13 seconds. Note that this damage magnitude is the closest to model No. 10 in Table I.

Now three approaches discussed in section 2 are compared with each other through simulations at the abovementioned conditions. Figure 7 shows mode switching information in FIMM. Before the fault time, the model probability of the normal mode has the highest value as shown in Fig. 7(a). However, after the fault, the model probability of the 10-th mode becomes the highest. Based on the model probability, mode number in Fig. 7(b) can declare that the damage magnitude is the closet to model No. 10.

Figure 8 shows mode number declaration in MMAC. At the fault time, the mode number can



(a) Model probability



(b) Mode number declaration

Fig. 7. Mode switching information in fuzzy-tuning IMM filter

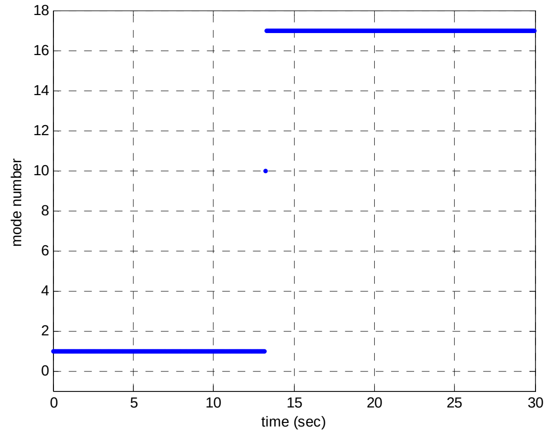


Fig. 8. Mode number declaration in multiple model adaptive control

declare that model No. 10 is the closet to the failure situation. After that, the system is reinitialized to mode No. 10. Therefore, two approaches based on multiple model: FIMM and MMAC can easily carry out the fault detection and diagnosis.

Figures 9-10 show the histories of state variables: sideslip and bank angle in each approach. There are fluctuations of both sideslip and bank angle near the fault time, 13 seconds. At this time, a controller switching is made from the normal model to the model No. 10 in FIMM. Also, a reinitialization to model No. 10 is made in MMAC. By these processes, command tracking performance can be maintained in FIMM and MMAC. However, there is a bias in bank angle of FIMM in Fig. 10(a). This is because the fault magnitude is not accurately same as that of the model No. 10. On the other hand, the system can follow reference command very well after the fault although MDAC does not have any parameter estimation and mode detection process as shown in Figs. 9(b) and 10(b).

Figures 11-12 show the control surface histories: rudder and aileron. The effort of control surfaces for reconfiguration can be seen after the fault in all approaches. There is a fast motion of control surfaces after the fault in MMAC. This comes from the fact that MMAC sensitively reflects the parameter variation due to system failure. Note that this method includes the parameter identification process.

Table II shows the comparative data of three fault tolerant control techniques. The command tracking error is the smallest in MMAC. The control energy in FIMM and MDAC is much smaller than MMAC. Especially, the control kinetic energy in MMAC is much higher than those of the other two approaches.

Table II. Comparative data without noise

	FIMM	MDAC	MMAC
$\lvert y - y_r \rvert$, deg	34.7	31.6	17.9
$\lvert u \rvert$, deg	180.9	178.7	279.9
$\lvert \dot{u} \rvert$, deg/s	82.3	47.6	4795.4

Let us consider process/output noises with a second-order butterworth low-pass-filter in adaptive control schemes. This degrades the command tracking performance in MDAC as shown in Table III. The command tracking error is still the smallest in MMAC. However, MMAC consumes much higher control energy than the others because it regards the noise as the parameter variation.

Table III. Comparative data with noise

	FIMM	MDAC	MMAC
$\lvert y - y_r \rvert$, deg	34.7	35.8	2.3
$\lvert u \rvert$, deg	180.9	181.4	326.7
$\lvert \dot{u} \rvert$, deg/s	82.3	60.9	9924.8

In short, it can be said that controller structure of FIMM is very simple and the noise characteristics is superior to the other approaches. Command tracking performance of adaptive controllers is better than that of FIMM. The computation load of MDAC is smaller than that of the others. However, the chattering problem of control surfaces in MMAC is very serious because their fast motion might lead to a structural breakage.

FIMM can give robust estimates to noise. At the same time, MDAC or MMAC can have better command tracking characteristics. Note that conventional Kalman filter cannot reflect the system change from the failure. Therefore, FIMM should be tightly connected with MDAC or MMAC to give robust state estimates despite of the system failure.

4 Conclusions

In this study, three fault tolerant controllers were considered for aircraft actuator failures. It is shown that each approach has its own merits and weaknesses through simulations with the same conditions. Especially, adaptive control techniques are very sensitive to noisy conditions. Adaptive techniques based on fuzzy-tuning IMM filter can be the solution to various noise conditions for a robust fault tolerant control.

Acknowledgement

This Research was supported by the Ministry of Science and Technology through the National Research Laboratory (NRL) program, Republic of Korea, under contact M1-0318-00-0028.

References

[1] J. Choi, S. Kim, and Y. Kim. Aircraft Fault Detection and Diagnosis Using Fuzzy-tuning IMM Filter. *KSAS-JSASS Joint International Symposium on Aerospace Engineering*, Nagoya, Japan, October 2005.

[2] K. Kim, K. Lee, and Y. Kim. Reconfigurable Flight Control System Design Using Direct Adaptive Method. *Journal of Guidance, Control, and Navigation*, Vol. 26, No. 4, pp. 543-550, 2003.

[3] C. Ahn. Design of Reconfigurable Flight Control System Using Output Error Feedback Based on Model Following Adaptive Control Scheme. MS Thesis, Mechanical and Aerospace Engineering, Seoul National University, Dec. 2003.

[4] B. Jung, S. Jeong, D. Lee, and Y. Kim. Adaptive Reconfigurable Flight Control System Using Multiple Model Mode Switching. *16th IFAC World Congress*, Prague, Czech Republic, July 2005.

[5] H. A. P. Bloom, and Y. Bar-Shalom. The Interacting Multiple Model Algorithm for Systems with Markovian Switching Coefficients. *IEEE Transactions on Automatic Control*, Vol. 33, No. 8, pp. 780-783, 1988.

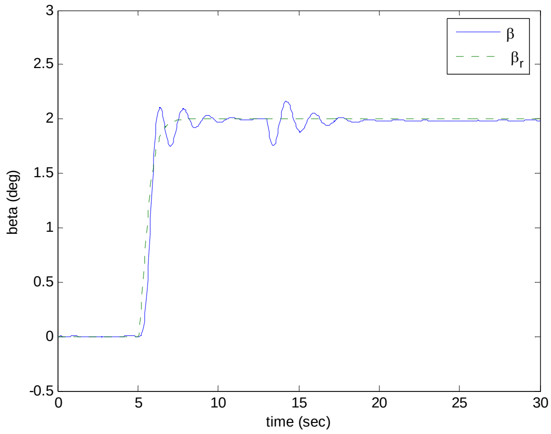
[6] J.–S. R. Jang, C.-T. Sun, and E. Mizutani. *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*. Prentice Hall, Englewood Cliffs, NJ, 1997.

[7] M. Bodson, and J. E. Groszkiewicz. Multivariable Adaptive Algorithms for Reconfigurable Flight Control. *IEEE Transaction of Control Systems Technology*, Vol. 5, No. 2, pp. 217-229, 1997.

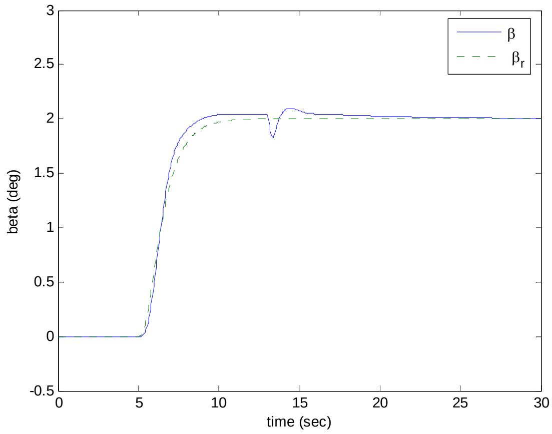
[8] T. Fujinaka, and S. Omatu. A Switching Scheme for Adaptive Control Using Multiple Models. *IEEE International Conference on Systems Man and Cybernetics*, Tokyo, Japan, Vol. 5, pp. 80-85, 1999.

[9] K. S. Narendra, and J. Balakrishnan, Adaptive Control Using Multiple Models. *IEEE Transactions on Automatic Control*, Vol. 42, No. 2, pp. 171-187, 1997.

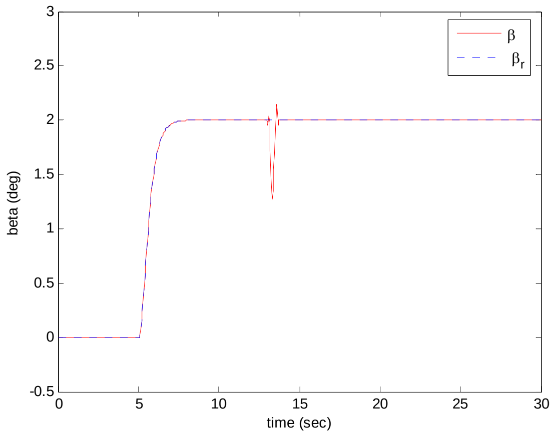
[10] D. Kim, and Y. Kim. Robust Variable Structure Controller Design for Fault Tolerant Flight Control. *Journal of Guidance, Control, and Dynamics*, Vol. 23, No. 3, pp. 430-437, 2000.



(a) Fuzzy-tuning IMM filter

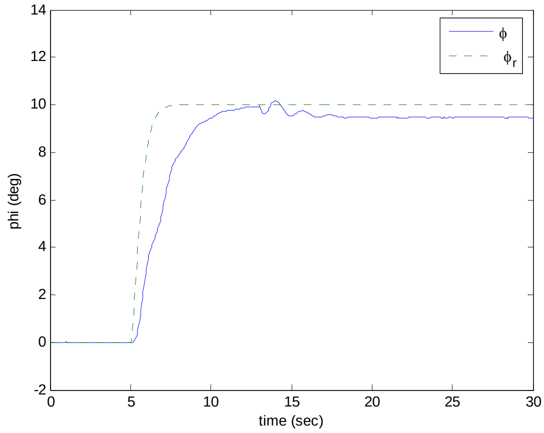


(b) Model-following direct adaptive control

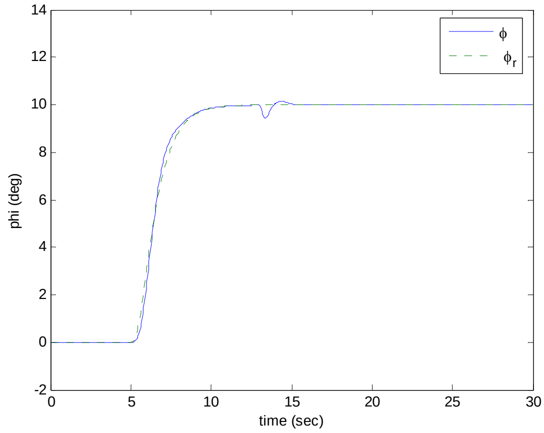


(c) Multiple model adaptive control

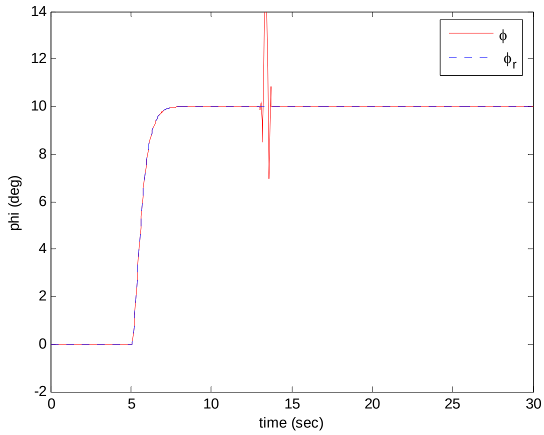
Fig. 9. Sideslip angle histories



(a) Fuzzy-tuning IMM filter

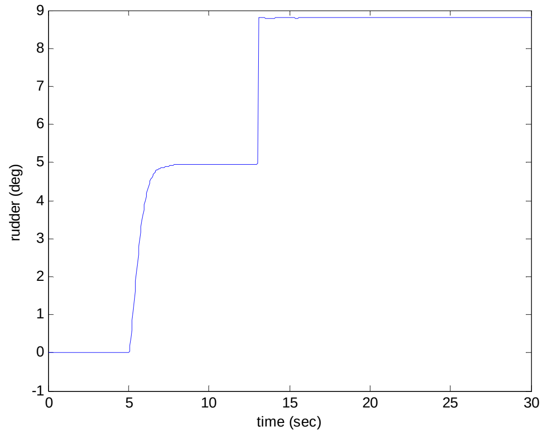


(b) Model-following direct adaptive control

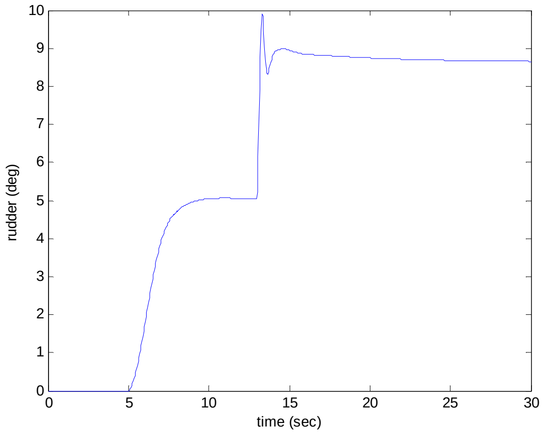


(c) Multiple model adaptive control

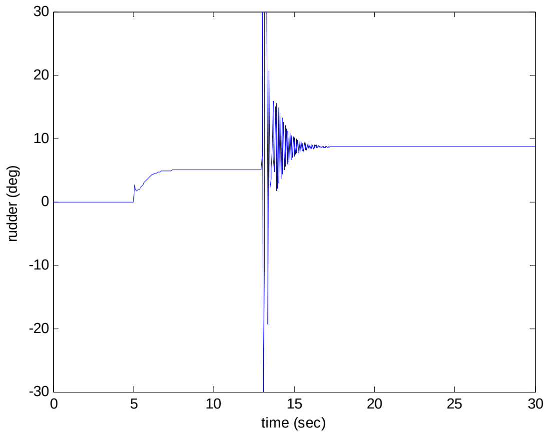
Fig. 10. Bank angle histories



(a) Fuzzy-tuning IMM filter

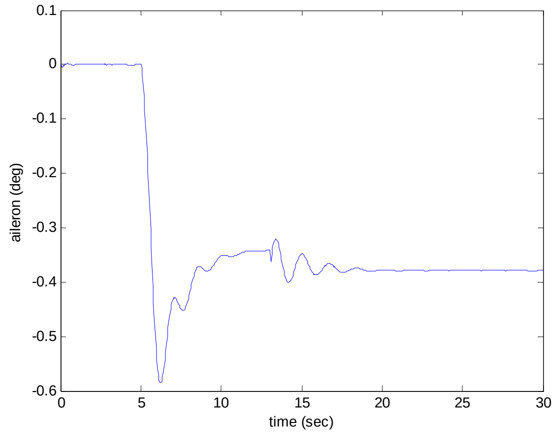


(b) Model-following direct adaptive control

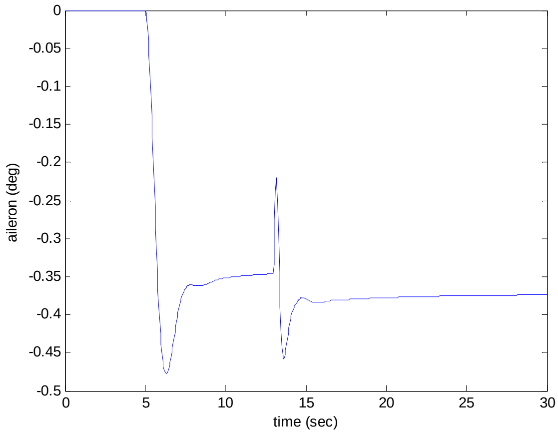


(c) Multiple model adaptive control

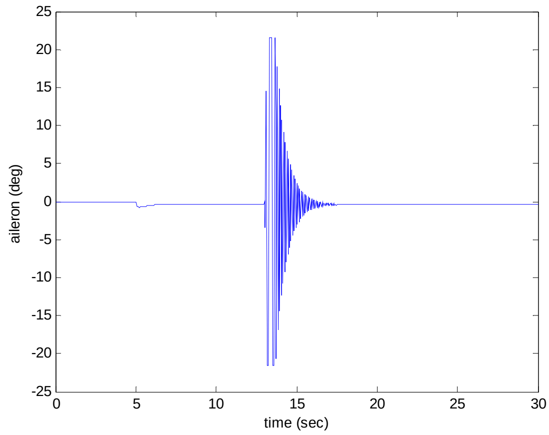
Fig. 11. Rudder angle histories



(a) Fuzzy-tuning IMM filter



(b) Model-following direct adaptive control



(c) Multiple model adaptive control

Fig. 12. Aileron angle histories