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Actuator Fault Decoupled Residual Generation on Lateral Moving Aircraft

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Abstract

Implementation of time-scheduled maintenance is not suitable if it is applied for systems with many varieties of heavy workload and harsh environment since on that condition components degrade earlier that those under normal condition. Therefore it has been shifted to condition-based maintenance (CBM). One important aspect, among others, toward implementation of CBM method is fault isolation. The problem investigated in this paper is related todecouple residual generation for actuator fault isolation of an aircraft on lateral movement. The proposed solution for that problem is to implement combination of transformation matrix and special filter. Transformation matrix is used to convert feature locations of actuator faults to signature vectors. Moreover, the signature vectors will be processed further by special filter to generate decoupled residuals. It is assumed that the actuator is the only fault when the aircraft is on lateral movement. The result showed that special filter and transformation matrix can be designed so that the residual of aileron actuator fault is decoupled from the residual of rudder actuator fault.

Keywords: *Fault detection, Decoupled residual, Aircraft modelling, Control system*

1. Introduction

The main objective of maintenance is to reduce the possibility of fatal system damage due to component failure, which can leads to material loss or even casualty. The earliest form of traditional maintenance is called the reactive maintenance. In this method, maintenance is conducted after a component is experiencing a failure. The next method of that is still commonly used is by performing periodic inspection to monitor the system condition. If the system is frequently subjected to heavy workload, then the component can experience premature degradation. This can lead to the failure of periodic inspection method to evaluate the system condition in timely manner, thus it is possible that the system is already experiencing undetected failure in between inspections, which leads to huge cost for replacing and repairing its components. Therefore a new method of maintenance which can monitor the system condition in real-time is needed. This requires the ability to detect the location of actuator component which experiences a failure.

One of the existing method of maintenance is based on statistical data [1]. Due to technological development, the system complexity tends to increase and operated on its maximum region for longer duration. Due to this, the system workload intensity and variation is increased which leads to increased cost for this method. Based on that observation, model based maintenance [2-3] is preferred for recent maintenance scheme. The main elements of model based maintenance is the capability to detect the existence of failure and its location.

The fault detection schemes based on artificial neural network has been previously proposed by several researcher. The main advantage of artificial neural network is its capability to learn. One of the previously proposed scheme is based on learning the possible fault signal with the goal of detecting similar failure during the system operation [4]. One of its earliest application is for diagnosing failure in robotic system [5]. The capability of artificial neural network has also been exploited to detect failure in multiple-sensor by learning the failure signature of each sensor [6]. Artificial neural network also has the advantage when learning new failure signature. However, its main drawback is it requires a learning period to build its knowledge of failure signatures. In case of fault detection and faultlocalization which requires fast response time, artificial neural network is not capable of detecting and localizing failure outside of its prior knowledge in short time.

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Another previously proposed method in this area is methods based on fuzzy logic. The main advantage of this scheme is it does not require detailed mathematical equations. As the mathematical equation commonly required to model the system condition is rather complex and requires specific modeling expertise and efforts. Previous scheme implements fuzzy logic for residual evaluation to detect failure in robotic systems [7]. Another example of fuzzy logic implementation in this field is its implementation on Takagi-Sugeno system model [8]. The disadvantage of fuzzy logic in fault detection and localization is it requires ad-ho rules for a specific system condition. The develpment of this ad-hoc rules requires significant domain knowledge which is not transferrable between problem domains.

To address the shortcoming of fuzzy logic implementation for fault detection and localization requires the system mathematical model to increase the applicability of this method to larger range of cases.Several works related to fault detection or fault lozalization/ isolation based on mathematical model can be seen in [9-10]. Meanwhile, to compensate the disadvantage of artificial neural network in fault detection and localization, i.e. its inability to handle fault signal which is not contained in its prior knowledge, the concept of vector with specific direction can beused. This scheme can be implemented by a combination of special filter and transformation matrix for multi-sensor fault detection in web winding system [11]. In this paper, those methods will be modified for the purpose of actuator fault localization, more specifically to generate residual signal from the aileron actuator and rudder actuator which are decoupled in laterally moving aircraft. The benefit of vector concept is it allows us to handle new form of fault signals which is previously unseen, as it only requires the direction of signature vector. The magnitude of signature vector is allowed to vary according to the form of failure, which increases the range of fault signal that it can handles. In other words, the direction of signature vector only corresponds to failure location. Which imply that it is possible to decouple the faultsignal residuals by designing the direction of signature vectors.

The main contribution of this paper is in the use of transformation matrix to restrict the fault signals into separate linear subspaces. The combination of transformation matrix and the specifc filter is designed to generate a dynamics of the filter error signal with separate dynamics for each failure modes. The filter output contains information regarding the actuator fault signal, system state signal, and system input signal. This signal is then further transformed by the transformation matrix to extract the actuator fault signal and convert it into a signature vector. The effectiveness of this method will be shown through design of a decoupled actuator fault detection and localization on laterally moving aircraft.

2. Proposed Method

2.1. Mathematical Model of Plant with Actuator Failure

A plant experienceing an actuator failure can be modeled as

$$\begin{aligned} \dot{\boldsymbol{x}}(t) &= \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}(t) - \boldsymbol{f}\boldsymbol{\mu}(t) \\ \boldsymbol{y}(t) &= \boldsymbol{C}\boldsymbol{x}(t) \end{aligned} \quad (1)$$

where $\boldsymbol{x}(t) \in R^n$ is the state vector, $\boldsymbol{y}(t) \in R^m$ is the output vector, and $\boldsymbol{u}(t) \in R^h$is the input vector. The actuator failure effects on the dynamics are modeled by an actuator location matrix$\boldsymbol{f}$ which is composed of columns of$\boldsymbol{B}$affected by the failures. The faultsignal is denoted by$\boldsymbol{\mu}(t)$.

2.2. Analysis of Decoupled Residual Generation for Actuator Fault Isolation

In this section, we discuss a modification of method proposed in [11], to handle actuator failure. To generate a residual vector, a special filter and transformation matrix $\boldsymbol{T}$ is required. The filter is used to generate filter error signal which contain the actuator fault signal among other signals. The transformation matrix is to convert the actuator failure location signature into a signature vector with fixed direction. The error signal is defined as,

$$\boldsymbol{e}(t) = \boldsymbol{s}(t) - \boldsymbol{T}\boldsymbol{x}(t) \quad (2)$$

where $\boldsymbol{e}(t)$ is the error signal and $\boldsymbol{s}(t)$ is the filter state. Therefore, the filter dynamic model can be written as,

$$\dot{\boldsymbol{s}}(t) = \boldsymbol{Es}(t) + \boldsymbol{Fy}(t) + \boldsymbol{G}u(t) \tag{3}$$

with $\boldsymbol{E}$ is the filter process matrix, $\boldsymbol{F}$ is a transformation matrix relating the value of system output and the filter states, and $\boldsymbol{G}$ is a transformation matrix relating the plant input and the filter states. The filter states is designed to capture the possible failure modes and related to the system states by the following equations,

$$\boldsymbol{s}(t) = \boldsymbol{Tx}(t) \tag{4}$$

One of the function of this specific filter is to generate the dynamics for the error signal between the filter output and the measured system states after transformations, $\boldsymbol{s}(t) - \boldsymbol{Tx}(t)$. This filter is designed such that in its steady state condition, the estimate error is zero if there is no failure. In the condition of failure, the special filter is designed to to generate decoupled residuals. The dynamic of filter error signal is given as,

$$\begin{aligned}\dot{\boldsymbol{e}}(t) &= \dot{\boldsymbol{s}}(t) - \boldsymbol{T}\dot{\boldsymbol{x}}(t)\\ &= \boldsymbol{Es}(t) + \boldsymbol{FCx}(t) + \boldsymbol{Gu}(t) - \boldsymbol{TAx}(t) - \boldsymbol{TBu}(t) + \boldsymbol{Tf\mu}(t)\end{aligned} \tag{5}$$

which can be rewritten as,

$$\dot{\boldsymbol{e}}(t) = \boldsymbol{Ee}(t) + (\boldsymbol{ET} + \boldsymbol{FC} - \boldsymbol{TA})\boldsymbol{x}(t) + (\boldsymbol{G} - \boldsymbol{TB})\boldsymbol{u}(t) + \boldsymbol{Tf\mu}(t) \tag{6}$$

In case of two actuator failures (denoted by $\boldsymbol{f_1}$ and $\boldsymbol{f_2}$), the error dynamics is equal to,

$$\dot{\boldsymbol{e}}(t) = \boldsymbol{Ee}(t) + (\boldsymbol{ET} + \boldsymbol{FC} - \boldsymbol{TA})\boldsymbol{x}(t) + (\boldsymbol{G} - \boldsymbol{TB})\boldsymbol{u}(t) + \boldsymbol{Tf_1\mu_i}(t) + \boldsymbol{Tf_2\mu_k}(t) \tag{7}$$

These equations imply that the filter response depends on the plant input, the plant state, and the fault signals. To ensure that the response only depends on the actuator fault signals, then the following conditions have to be fulfilled,

$$\boldsymbol{ET} + \boldsymbol{FC} - \boldsymbol{TA} = 0 \tag{8.1}$$

$$\boldsymbol{G} - \boldsymbol{TB} = 0 \tag{8.2}$$

Under these conditions, the error dynamics become,

$$\dot{\boldsymbol{e}}(t) = \boldsymbol{Ee}(t) + \boldsymbol{Tf_1\mu_i}(t) + \boldsymbol{Tf_2\mu_k}(t) \tag{9}$$

Taking a special case where $\boldsymbol{E}$ is a diagonal matrix, then it implies that,

$$[\boldsymbol{Tf_1} \quad \boldsymbol{Tf_2}] = \boldsymbol{I}_2 \tag{10}$$

where $\boldsymbol{I}_2$ is an identity matrix with two diagonal components. Each of the identity matrix columns is taken as the signature vectors.

2.3. Transformation Matrix Calculation

Our main contribution in this work is the introduction of transformation matrix which decouples the error signal. In this section we will discuss the details of calculation for this transformation matrix. From equation 6, it can be observed that matrix $\boldsymbol{A}$is composed of m rows and n columns, while matrix $\boldsymbol{C}$ is composed of m rows and n columns. Matrix $\boldsymbol{C}$is assumed to directly measure m state variables, such that $\boldsymbol{C} = [\boldsymbol{I_m} \quad \boldsymbol{0}]$. Matrix$\boldsymbol{A}$ can be denoted as $\boldsymbol{A} = [\boldsymbol{A_1} \quad \boldsymbol{A_2}]$ with $\boldsymbol{A_1}$ is a $n \times m$ matrix, while matrix$\boldsymbol{A_2}$ is a $n \times (n-m)$ matrix. As $\boldsymbol{E}$can be designed as a diagonal matrix, then eq. 8.1 can be separated into two parts [12],

$$(TA - ET)\begin{bmatrix} I_m \\ 0 \end{bmatrix} = FC \tag{12}$$

$$(TA - ET)\begin{bmatrix} 0 \\ I_{n-m} \end{bmatrix} = 0$$

Due to the diagonal structure of $\boldsymbol{E}$ then for each eigenvalue of $\boldsymbol{E}$, the following equality holds

$$T_i^T \left[A_2 - \lambda_i \begin{bmatrix} 0 \\ I_{n-m} \end{bmatrix} \right] = 0 \tag{13}$$

which to simplify the notation can be written as,

$$T_i^T L_i = 0. \tag{14}$$

The vector $\boldsymbol{T_i^T}$ is the i-th rowof matrix $\boldsymbol{T}$. From the discussion, we can observe that $\boldsymbol{T_i^T}$ is an element of the left nullspace of matrix $\boldsymbol{L_i}$. Therefore, the bases for left nullspace of $\boldsymbol{L_i}$ needs to be determined to calculate the value of $\boldsymbol{T_i^T}$. As in general $\boldsymbol{L}$ is not a square full-rank matrix, the left null-space will have to be calculated by utilizing the SVD (Singular Value Decomposition) algorithm [13]. It implies that there exists d_{ij} such that the row vector $\boldsymbol{T_i^T}$ can be written as,

$$\boldsymbol{T_i^T} = \sum_{\boldsymbol{j=1}}^{\boldsymbol{r}} \boldsymbol{d_{ij}}\, \boldsymbol{h_{ij}^T} \tag{15}$$

where $\boldsymbol{h_{ij}^T}$ is the j-th basis of the left nullspace of the $\boldsymbol{L_i}$ matrix, r is the dimension of the left nullspace. This relation allows us to express equation 9 as,

$$[d_{i1} \;\; \dots \;\; d_{ir}] \begin{bmatrix} h_{i1}^T \\ \vdots \\ h_{ir}^T \end{bmatrix} [f_1 \;\; f_2] = q_i \tag{16}$$

with $\boldsymbol{q_i}$ is the i-th column of identity matrix. The relation shows that each $\boldsymbol{T_i^T}$ can be calculated independently, which leads to easier computation procedure.

2.4. Mathematical Model of Laterally Moving Aircraft

The derivation of mathematical model for laterally moving aircraft has been previously studied in [14]. The model is derived for a very large four-engined, passenger jet aircraft CHARLIE operating at 6100m height moving laterally with 0.8 mach airspeed can be modeled as a linear system,

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}(t), \boldsymbol{y}(t) = \boldsymbol{C}\boldsymbol{x}(t) \tag{17}$$

with,

$$\boldsymbol{C} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{18}$$

$$\boldsymbol{A} = \begin{bmatrix} -0.12 & 0 & -1 & 0.04 \\ -4.12 & -0.98 & 0.29 & 0 \\ 1.62 & -0.016 & -0.232 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{19}$$

$$\boldsymbol{B} = \begin{bmatrix} 0 & 0.014 \\ 0.31 & 0.18 \\ 0.013 & -0.92 \\ 0 & 0 \end{bmatrix} \tag{20}$$

2.5. Fault Detection Filter and Transformation Matrix Design

It can be observed from matrix $\boldsymbol{A}$ that the state space dimension of the model (n) is equal to four, while the number of output signal can be observed from matrix $\boldsymbol{C}$ (m) to be equal to two. The input to the system is represented by the two columns of $\boldsymbol{B}$, with the first column corresponds to the aileron while the second column corresponds to the rudder. As it implies that there might be two sources of disturbance (fault signal), then the fault detection filter dimension (k) is designed to be two. To ensure the stable convergence of the error between the estimated filter output and transformed state space, the eigenvalues of the fault detection filter matrix must have negative real value, which is designed to be at $\lambda_1 = -10$ and $\lambda_2 = -12$. Following the previous discussion in section 3.A, the algorithm for filter design can be performed according to the pseudocode given in algorithm 1.

$$
\begin{aligned}
&\mathit{Algorithm1: Fault\ Detection\ Filter\ Design}\\
&\quad [\boldsymbol{T},\boldsymbol{E},\boldsymbol{F},\boldsymbol{G}] = \text{faultDetectionFilter}(\boldsymbol{A},\boldsymbol{B},\boldsymbol{C},\boldsymbol{f},\boldsymbol{\lambda},n,m,k)\\
&\quad \mathit{for}\ i = 1{:}k\\
&\qquad [\boldsymbol{H},\sim,\sim] = \text{SVD}\left(\boldsymbol{A_2} - \lambda_i \begin{bmatrix} 0 \\ \boldsymbol{I_{n-m}} \end{bmatrix}\right)\\
&\qquad \boldsymbol{h_i} = \boldsymbol{H_{n\times(m+1;n)}}\\
&\qquad \boldsymbol{T_i} = (\boldsymbol{h_i}(\boldsymbol{f^T}\boldsymbol{h_i})^{-1}\boldsymbol{I_i})^{\boldsymbol{T}}\\
&\quad \mathit{end}\\
&\quad \boldsymbol{E} = \text{diag}(\boldsymbol{\lambda})\\
&\quad \boldsymbol{F} = (\boldsymbol{TA} - \boldsymbol{ET})\begin{bmatrix} \boldsymbol{I_m} \\ \boldsymbol{0} \end{bmatrix}\boldsymbol{C^{-1}_{m\times(1;m)}}\\
&\quad \boldsymbol{G} = \boldsymbol{TB}\\
&\mathit{end}
\end{aligned}
$$

Using the model of lateral moving aircraft and the designed eigenvalue as the input to the algorithm genereates the following transformation matrix $\boldsymbol{T}$ and fault detection filter matrix $\boldsymbol{F}$,

$$\boldsymbol{T} = \begin{bmatrix} 8.2587 & 3.1943 & 0.7507 & -0.033 \\ -15.4081 & 0.055 & -1.3107 & 0.0514 \end{bmatrix}, \tag{21}$$

$$\boldsymbol{F} = \begin{bmatrix} 69.6518 & 28.7678 \\ -185.3975 & 0.678 \end{bmatrix}, \tag{22}$$

while the filter input matrix G is equal to,

$$\boldsymbol{G} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}. \tag{23}$$

3. Research Method

To show the performance of the designed fault detection filter and transformation matrix, in this section we will perform comparison between conventional fault detection method based on comparison between the measured state and the estimated state represented in Figure 1 and the proposed fault detection filter with transformation matrix represented in Figure 2.

In both of the simulated schemes, the aircraft dynamics is represented by the upper blocks, while the lower block represents the fault detection schemes. In the conventional scheme, as the comparison is done in the subspace of system output, there is no guarantee of decoupling between fault signals. While in our proposed method, the comparison is done between the estimated states and the fault detection filter on the subspace selected by transformation matrix. Therefore, we can design the transformation matrix to give error signal $\boldsymbol{e}(\boldsymbol{t})$ which deliberately separates the fault signal as can be seen in equation 9 and equation 10. For fault reconstruction purpose, each error signal $\boldsymbol{e_i}(t)$ is magnified by the corresponding eigenvalue λ_i.

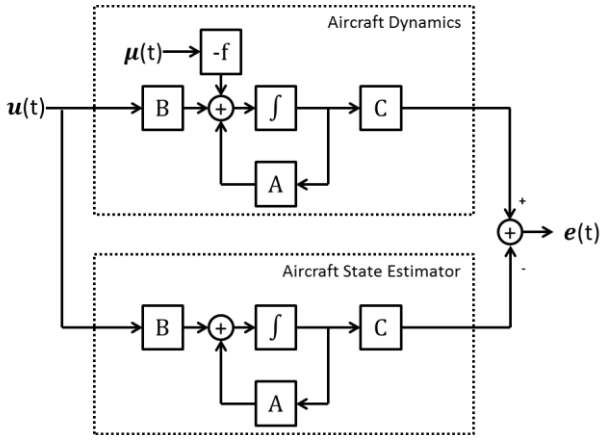

Figure 1. Conventional Fault Detection Method Based on Comparison between Measured State and Estimated State

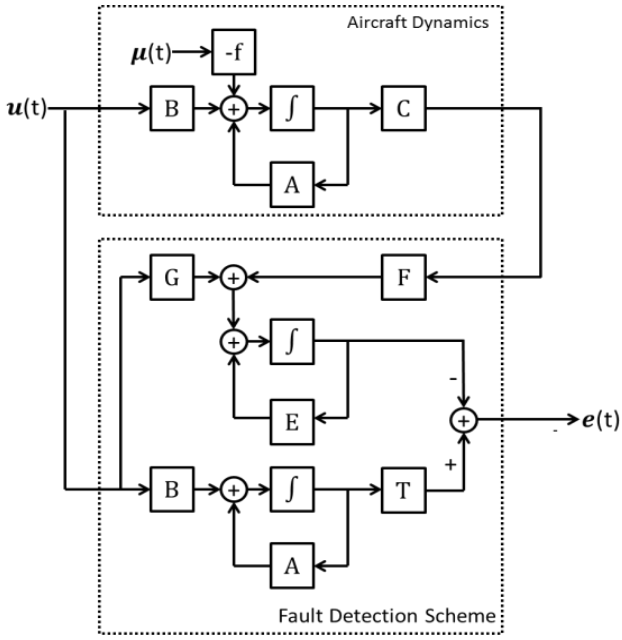

Figure 2. The Proposed Fault Detection Scheme, Fault Signal Generation Performed Between Filtered Measured State and Estimated State in the Transformation Matrix Subspace

4. Results and Analysis

The numerical simulation results are shown in Figure 3. The simulation is performed using backward Euler as the discritization method with a time step of 0.001 seconds where the numerical value of the model is given in eq.18-23. The system is given a constant vector of $[0.1\ \ 0.2]^T$ as its input, and the state value of all zeros as its initial condition. The fault signal is given in Figure 3.b in which the fault signal is composed of a step signal for the aileron and the oscillating signal in the rudder. Due to this fault signal, the output which should be composed of decaying sinusoids converging to the given input signals are continuously oscilliating as it can be observed in Figure 3.a.

The main aim of fault detection method is to detect the existence of this fault signal. The performance of both conventional fault detection method and the proposed fault detection method is given in Figure 3.c and Figure 3.d. First of all, it can be observed that both methods are effective in detecting the existence of faults, as we can see that both methods generate nonzero value which indicates the existence of fault. However, the output of conventional fault detection method as shown in Figure 3.c only manages to detect the existence of fault. The proposed fault detection filter in Figure 3.d manages to reconstruct the fault signature signal and decouple the signals (fault isolation). This result shows the effectiveness of our proposed method.

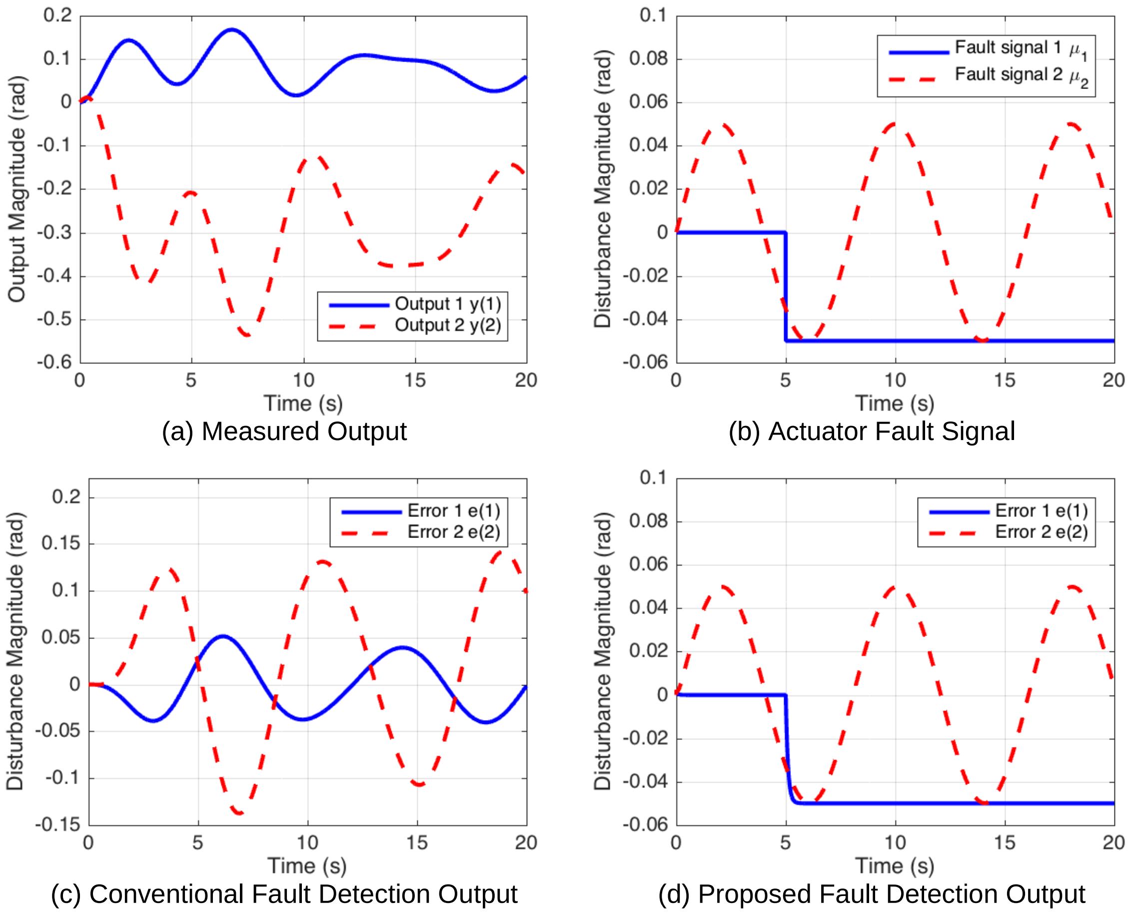

Figure 3. Simulation Results of the Conventional Fault Detection Method and the Proposed Method

From Figure 3.d, both the step fault signal and the oscillatingfault signal can be reconstructed faithfully as shown by the continuous line and the dashed line respectively. It can be seen that the reconstructed step signal has a fast exponential change rather than an idealstep change. This corresponds to the dynamics of the reconstructed aileron fault signal given by the chosen eigenvalue $\lambda_1 = -10$. On the other hand, careful observation suggests that the reconstructed oscillating fault signal has a slightly shifted phase compared to the actual oscillating fault signal in the rudder which is caused by the chosen eigenvalue $\lambda_2 = -12$. In this simulation, it is true that for more accurate fault signal reconstruction, the eigenvalues of matrix $\boldsymbol{E}$can be chosen to have larger negative values. However, larger negative eigenvalues will result in the fault detection filter becoming more sensitive to noise, hence in practice, the eigenvalues of matrix $\boldsymbol{E}$ needs to be carefully chosen.

5. Conclusion

In this work, a method to design fault detection filter and transformation matrix $\boldsymbol{T}$ is proposed. The introduction of transformation matrix improves the conventional fault detection filter by allowing it to completely decouple the fault signal. The effectiveness of this method is shown by an example of fault detection filter and transformation matrix design to decouple the fault signal on a lateral moving aircraft model. The simulation results showed that the design is able to decouple the aileron residual fault signal and rudder residual fault signal which leads to actuator fault isolation. Some interesting future works would be to combine this novel capability of fault signal decoupling with the control system capability to adapt to fault signal to design a reconfigurable control system.

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