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Fault Detection, Isolation and Adaptive Augmentation for Incremental Backstepping Flight Control

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Abstract: Uncertainties caused by unforeseen malfunctions of the actuator or changes in aircraft behavior could lead to aircraft loss of control during flight. The paper presents a Two-Layer Framework (TLF) augmenting Incremental Backstepping (IBKS) control algorithm designed for an aircraft. IBKS uses angular accelerations and current control deflections to reduce the dependency on the dynamics model. Nevertheless, knowledge of the control effectiveness is still required for proper tracking performance and stability guarantee and becomes essential in a case of failure. The proposed TLF is designed to detect possible problems such as a failure or presence of unknown actuator dynamics and to adapt the control effectiveness. At the first layer, the system performs detection and isolation of possible failures. After a problem being detected and isolated, the algorithm initiates the second-layer adaptation of the individual effectiveness of the failed control effector. For some critical scenarios, when the input-affine property of the IBKS is violated, e.g., for a combination of multiple failures, the IBKS could lose stability. Meanwhile, the proposed TLF-IBKS algorithm has improved tracking and stability performance.

Keywords: On-line dynamics identification; Fault detection and isolation; Aircraft dynamics, control; Incremental Backstepping; Unmodeled dynamics.

1. INTRODUCTION

Enabling flight safety of passenger aviation in possible abnormal conditions, such as those caused by equipment failures and/or adverse environmental factors, is a vital problem. Analysis of accident and incidence reports revealed that the main contribution to the fatal accidents was due to aircraft Loss of Control In-Flight and Controlled Flight Into Terrain. The main reasons caused these accidents are pilot mistakes, technical malfunctions, or their combination. Recently, great efforts have been undertaken to improve flight safety (Ignatyev *et al.*, 2017; Ignatyev and Khrabrov, 2018; Abramov *et al.*, 2019).

Failures of control surface can cause a dramatic change in flight dynamics. Fault Tolerant Control (FTC) strategies can help to recover control capabilities. The FTC strategies can be classified into passive and active approaches (Alwi, Edwards and Tan, 2011). In the passive approach, the control algorithm is designed so that the system can achieve its given objectives, in fault-free as well as in faulty situations (Patton, 1997). However, achieving robustness is often possible at the expense of decreased nominal performance. The active approaches react to fault events by using a reconfiguration/accommodation mechanism to compensate the effect of faults either by selecting a pre-computed control law or by designing a new control strategy online (Zhang and Jiang, 2008).

Incremental Backstepping (IBKS) control approach demonstrates adaptive abilities itself, so a change in aircraft dynamics can be partially compensated (Sun *et al.*, 2013). However, amended control effectiveness will introduce error in the system that cannot be fully compensated by the IBKS and could cause stability and performance degradation (van Gils *et al.*, 2016), especially when input-affine property of the IBKS is lost.

The novelty introduced by the paper is a new model-free approach for active FTC obtained by augmentation of IBKS flight control with a Two-Layer Framework (TLF) performing fault detection and isolation (FDI) for control effectors and adaptation of the control effectiveness. The proposed technique augmenting IBKS flight control improves control performance in case of failures or unmodeled actuators dynamics. A two-layer structure is a key feature of the proposed technique. At the first layer, possible degradation of aircraft dynamics is observed and the FDI is performed. At the second layer, new values of control effectiveness for the failed effectors are estimated. The concept is tested using a nonlinear model of large transport aircraft Boeing 747. Two different types of failures of elevators are considered, namely, hardover and unmodeled actuator dynamics.

The paper is organized as follows. A very brief overview of the IBKS is provided in Section 2. A general structure of the two-layer structure is discussed in Section 3. The first and second layers are presented in Sections 4 and 5. The simulation results are given in Section 6. Finally, Section 7 concludes the study.

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2. INCREMENTAL BACKSTEPPING

Sensor-based technique utilizing Incremental Dynamics (ID) is applied in (Cordeiro, Azinheira and Moutinho, 2019) to obtain the IBKS controller, which is less dependent on the system model. IBKS computes incremental commands employing acceleration feedback estimations to extract unmodeled dynamics information. In the present study, we are using this controller as a baseline controller, which is augmented with the TLF on-line parameter estimation routine. Below, we will just provide a brief description of the controller. Details could be found in the original paper.*Incremental dynamics model*

An aircraft flight dynamics model can be represented in the following form:

$$\dot{\mathbf{x}} = \mathbf{f}_{\mathbf{x}}\left(\mathbf{x},\mathbf{u}\right) \tag{1}$$

where $\mathbf{f}_{\mathbf{x}}$ is a continuous function, $\mathbf{x}$ and $\mathbf{u}$ are the state and the control input vectors. Expanding (1) into the Taylor series around $\left(\mathbf{x}_0,\mathbf{u}_0\right)$ corresponding to the previous time moment t_0 the dynamics (1) can be expressed in the following form

$$\dot{\mathbf{x}} \cong \dot{\mathbf{x}}_0 + \frac{\partial \mathbf{f}_{\mathbf{x}}\left(\mathbf{x},\mathbf{u}\right)}{\partial \mathbf{x}}(\mathbf{x}-\mathbf{x}_0) + \frac{\partial \mathbf{f}_{\mathbf{x}}\left(\mathbf{x},\mathbf{u}\right)}{\partial \mathbf{u}}(\mathbf{u}-\mathbf{u}_0)\,. \tag{2}$$

Assuming that the increment in state $\Delta\mathbf{x} = \mathbf{x}-\mathbf{x}_0$ is much smaller than the increment in both state derivative $\Delta\dot{\mathbf{x}} = \dot{\mathbf{x}}-\dot{\mathbf{x}}_0$ and input $\Delta\mathbf{u} = \mathbf{u}-\mathbf{u}_0$, the dynamics (2) can be simplified

$$\Delta\dot{\mathbf{x}} \cong B_0\,\Delta\mathbf{u}\,, \tag{3}$$

where $B_0 = \dfrac{\partial \mathbf{f}_{\mathbf{x}}\left(\mathbf{x},\mathbf{u}\right)}{\partial \mathbf{u}}$ is a control effectiveness matrix.

The dynamics equation in the form (3) articulates that incremental dynamics of the system is produced by the control input increment. For the implementation of such a concept, it is assumed that sampling time is small. In this case, the assumption that $\Delta\mathbf{x} \ll \Delta\dot{\mathbf{x}}$ and $\Delta\mathbf{x} \ll \Delta\mathbf{u}$ becomes possible for the real aircraft because the control surface deflections directly affect the angular accelerations, whereas the angular rates only change by integrating these angular accelerations. Actuators are assumed to be very fast such that the demanded input increment can be achieved within the small sampling time. In addition, the sensors are assumed to be ideal.

2.2 Cascaded Incremental Backstepping

The ID idea combined with the backstepping paradigm yields the IBKS controller. To improve robustness and simplify its implementation, both angle and rate control using ID was formulated. A high-level structure of the IBKS control system is given in Fig.1.

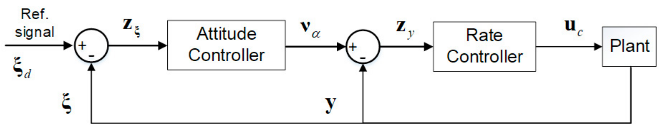

Fig.1. IBKS structure (adopted from (Cordeiro, Azinheira and Moutinho, 2019))

To design the cascaded controller, the equations of motions were separated into two subsystems, namely, into kinematics and dynamics subsystems. At the first step, to design the angular controller, the knowledge of kinematics was preplaced by the measurements of the attitude state derivative $\dot{\xi}_0$. At the second step, to design the second IBKS controller for the rate control, the dynamics equations were partially replaced by evaluations of angular rate derivatives. The general idea behind the backstepping is to consider the state vector $\mathbf{v}_\alpha = \boldsymbol{\omega} = \left[p \;\; q \;\; r\right]^T$ from the dynamics subsystem as a control input to the kinematics subsystem. Since $\boldsymbol{\omega}$ is just a state variable and not the real control input, it is called a virtual control input. The airspeed was introduced as a state to the second controller in order to design the rate controller which simultaneously tracks the airspeed and angular rates of the aircraft.

The final control law was designed to guarantee the asymptotic convergence of the dynamics state $\mathbf{y} = \left[V_t \;\; \boldsymbol{\omega}^T\right]^T$ towards the desired value $\mathbf{y}_d = \left[V_{td} \;\; \mathbf{v}_\alpha^T\right]^T$. Finally, the baseline controller had the following form:

$$\mathbf{u}_c = \mathbf{u}_0 + B_0^{-1}\Lambda\left(aC_{y\omega}^T T_\xi^T \mathbf{z}_\xi + W_y(\mathbf{y}_d - \mathbf{y}) + \dot{\mathbf{y}}_d - \dot{\mathbf{y}}_0\right) \tag{4}$$

Here a is a design factor, $C_{y\omega} = \left[\mathbf{0}_3 \;\; \mathrm{I}_3\right]$ is a selection matrix such as $\boldsymbol{\omega} = C_{y\omega}\mathbf{y}$, W_y is a design weight matrix, $\mathbf{z}_\xi = \xi_d - \xi$ is a kinematics error vector, ξ_d is a desired kinematics state vector. The matrix

$$\mathbf{T}_\xi = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ \sin\alpha & 0 & -\cos\alpha \end{bmatrix},$$

gives the relationship between the angular rate vector $\boldsymbol{\omega}$ and the kinematics state vector.

To attenuate the measurement noise and increase the control robustness, B_0 is multiplied by a diagonal matrix $\Lambda > 0$ with elements $\lambda_{ii} \in [0,1]$.

3. TWO-LAYER FRAMEWORK ROUTINE

According to (4) the IBKS requires accurate knowledge of the control effectiveness. This information is essential in the case of a control effector failure. The current section introduces the TLF that detects, isolates anomalies and estimates the control derivatives when uncertainties are in the actuation system (Fig.2). These estimates are used for adjustment of the control effectiveness matrix B_0. TLF uses measurements of aircraft states and control surface positions.

The first layer of the system is designed for FDI of a control effector. If a failure is detected the adaptive element of the second layer is initiated to estimate a new value of the control effectiveness. At the same time, the second layer demands identification manoeuvers for proper excitations of the system.

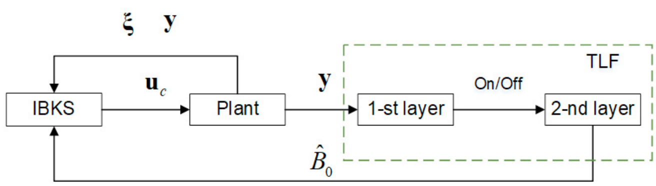

Fig.2. TLF-IBKS structure

4. FIRST LAYER OF FRAMEWORK

Different control surface faults produce different effects on the flight dynamics and thus different approaches should be used for FDI. Generally, a fault could cause a change in the aerodynamic effectiveness and/or change the dynamics of the actuator. So, it is typical to divide the FDI into aerodynamic FDI and actuator FDI (Swain and Manickavasagar, 2010). The first one is designed for the detection of aerodynamic anomalies, while the second one relates to actuator dynamics anomalies.

4.1 Aerodynamic FDI

For many cases, a fault of a control surface causes a change in aerodynamic effectiveness. In this case, a possible failure could be detected via generation of an innovation process, which is defined as the difference between the actual combined effectiveness and the expected one based on the model and the previous output data (Mehra and Peschon, 1971). It is called the innovation process since it represents the new information brought by the latest observation. Under normal conditions, the error signal is "small" and corresponds to random fluctuations in the output since all the systematic trends are eliminated by the model. However, under faulty conditions, the error signal is "large" and contains systematic trends because the model no longer represents the physical system adequately (Ignatyev, Shin and Tsourdos, 2019b).

4.2 Combined effectiveness estimation

The combined effectiveness for one of the control directions (roll (p), pitch (q) and yaw (r)) can be estimated from the regression model

$$\boldsymbol{\zeta}_m \cong \mathbf{A}_m \hat{\theta}_m ,\ m = V_t, p, q, r , \tag{5}$$

where $\boldsymbol{\zeta}_m = \left[\Delta\dot{\mathrm{x}}_{m_{t-N}} \dots \Delta\dot{\mathrm{x}}_{m_{t-1}}\ \Delta\dot{\mathrm{x}}_{m_t}\right]^T$ is the response variable vector, which is composed of the record of incremental state vector derivative for m component of the dynamics state vector $\mathbf{y}$, $\mathbf{A}_m = \left[\Delta\mathrm{u}_{m_{t-N}} \dots \Delta\mathrm{u}_{m_{t-1}} \Delta\mathrm{u}_{m_t}\right]^T$ is a predictor variable vector, which is composed of the incremental input of the combined effector in m direction. The estimated combined effectiveness $\hat{\theta}_m$ is compared with the expected effectiveness, based on the current information of the control effectiveness

$$\bar{\theta}_m(t) = \sum_{i=1}^{N_u} \hat{\mathrm{b}}_{m_i} \Delta u_i(t) \Big/ \sum_{i=1}^{N_u} \Delta u_i(t) , \tag{6}$$

where $\hat{\mathrm{b}}_{m_i}$ is the estimation of individual effectiveness of control effector i in m direction obtained in the previous periods, u_i is the control input of the effector i at the time moment t, N_u is the number of effectors. It is assumed that at least one effector is available for each of the control direction m.
The modified Exponential Forgetting Recursive Least Squares (EF RLS) (Shin and Lee, 2020) is used for the estimation of the combined effectiveness from.

4.3 T-statistics

T-statistics is commonly used as a measurable criterion for decision making (Anderson, 2003):

$$T_{stat} = \left(\bar{X} - \mu_{st}\right) / \left((\sigma_{st} + b) / \sqrt{n}\right), \tag{7}$$

where $\bar{X}$ is the sample mean from a sample $X_1, X_2, ..., X_n$ of size n, and, σ_{st} is the estimate of the standard deviation of the data, and is the population mean. For the current study, $X_1, X_2, ..., X_n$ are time series of the combined effectiveness estimates, $\mu_{st} \triangleq \sum_{i=1}^{N_u} \hat{\mathrm{b}}_{m_i} \Delta u_i(t) / \sum_{i=1}^{N_u} \Delta u_i(t)$ is the estimation of the combined effectiveness based on the previous observations. A bias b is introduced to increase the tolerance of the detection procedure to "small" errors of the identification algorithm. Conventionally, a significance level $\alpha = 5$ is used.
The proposed statistics is tested against two hypotheses:

$$H_0 : t < t_{\alpha/2}, H_1 : t \ge t_{\alpha/2} , \tag{8}$$

The following interpretation can be obtained as a result of testing (8):

(1) Rejecting H_0 (accepting H_1): there is significant evidence that the error is not zero and the error can be due to a fault.
(2) Keeping H_0: we do not have enough evidence to believe that there is a fault.

The criterion (8) is effective in the detection of the presence of non-linear dynamics or degradation of the effectiveness.

4.4 Actuator FDI

At the current study, it is assumed that measurements of the control surface positions are available. In this case, such information can be used to detect and isolate a failure. In particular, the correlation between the measured control surface position and those demanded by the baseline controller is utilized for the actuator FDI

$$v_i = \rho\left(\Delta\mathbf{u}_{i_{meas}} \Delta\mathbf{u}_{i_{dem}}\right), \tag{9}$$

where $\Delta\mathbf{u}_{i_{meas}} = [\Delta u_{i_{t-N_{corr}}} \Delta u_{i_{t-N_{corr}+1}} \ldots \Delta u_{i_t}]\Big|_{meas}$ and $\Delta\mathbf{u}_{i_{dem}} = [\Delta u_{i_{t-N_{corr}}} \Delta u_{i_{t-N_{corr}+1}} \ldots \Delta u_{i_t}]\Big|_{dem}$ are the measured and demanded control increment, where N_{corr} is the length of the analysis set.

For each control surface i, statistics (9) is tested against two hypotheses:

$$H_0^{v_i} : v_i < v_{i_\beta}, H_1^{v_i} : v_i \geq v_{i_\beta}, \tag{10}$$

The following interpretation can be obtained as a result of testing (10):

(1) Rejecting $H_0^{v_i}$ (accepting $H_1^{v_i}$): there is significant evidence that the error is not zero and the error can be due to a fault in effector i.

(2) Keeping $H_0^{v_i}$: we do not have enough evidence to believe that there is a fault in effector i.

5. SECOND LAYER OF IDENTIFICATION

If the system detects any deviation from the nominal operational regime at the first layer, the system steps down to the second layer of identification where the individual effectiveness of the failed effector is estimated and adapted.

5.1 Control signal formation

To distinguish the effect produced by the effector under study, the aircraft is demanded to perform manoeuvers with reduced efforts of other control effectors that are redundant to the studied one. The control signal is divided into two signals, the first one is for the treated control effector, the second is a supporting signal. W_s is the weight matrix defining the reduction of the control efforts of the supporting control signal as compared to the nominal one. For example, Boeing 747 has four redundant elevators; if one of four elevators is under investigation, the coefficients in W_s of all other three elevators are decreased. It should be noted that if the supporting signal $\mathbf{u}^{\sup}$ is too large the identification signal is not distinguishable from the supporting one. At the same time, if it is too small, the control authority is not enough to guarantee the stability. Therefore, there is a trade-off between observability of identified parameters and ensuring stability during identification. Here, we propose the total control authority of the supporting signal to be equal to that of the identification signal $\sum_{i\neq k} W_{s_i}\hat{B}_{ij} = \hat{B}_{kj}$, where k is effector under study, j is the control direction. This is motivated by the consideration that the effectiveness of all supporting effectors should be not less than the studied elevator effectiveness in order to provide required authority from the stability point of view. At the same time, for the values $\sum_{i\neq k} W_{s_i}\hat{B}_{ij} > \hat{B}_{kj}$, the supporting signal is high and might distort the useful signal.

5.2 Individual identification

In the present section, the approach for identification of individual component in the control effectiveness matrix $\hat{B}_{\mathbf{0}}$ is described. The system dynamics could be represented in the form of incremental dynamics equation (3). Similar to (Ignatyev, Shin and Tsourdos, 2019a) it is assumed here that there is a vector $\boldsymbol{\theta}_j$ such that j-column of the $\hat{B}_{\mathbf{0}}$ could be represented as

$$\hat{\mathbf{b}}_j = \boldsymbol{\Phi}_j^T(\mathbf{x},\mathbf{u})\,\boldsymbol{\theta}_j, j = n, \tag{11}$$

where n is the number of the control effectors. $\boldsymbol{\Phi}_j^T(\mathbf{x},\mathbf{u})$ is the regressor function, $\boldsymbol{\theta}_j$ is the unknown vector of parameters to be identified. Below we will omit the subscript j for the sake of simplicity.

At a time moment k, the following measurement equation can be introduced by using past N measurements:

$$\boldsymbol{\zeta} \cong \mathbf{A}\,\hat{\boldsymbol{\theta}},$$

where $\boldsymbol{\zeta} = \left[\left(\Delta\dot{\mathbf{x}}_{k-N}\right)_{res} \ldots \left(\Delta\dot{\mathbf{x}}_{k-1}\right)_{res} \left(\Delta\dot{\mathbf{x}}_{k}\right)_{res}\right]^T$ is the observed variable, where $\left(\Delta\dot{\mathbf{x}}_{t-i}\right)_{res} = \Delta\dot{\mathbf{x}}_{t-i} - \hat{B}_0\left(\mathbf{x}_0,\mathbf{u}_0\right)\Delta\mathbf{u}_{t-i}^{\sup}$, $i = 0 \ldots N$, is the pure dynamics produced by a treated control effector m. $\mathbf{A} = \left[\Delta \mathrm{u}_{ind_{t-N}} \ldots \Delta \mathrm{u}_{ind_{t-1}} \Delta \mathrm{u}_{ind_t}\right]^T$ is the predictor variable vector. The unknown parameter $\hat{\boldsymbol{\theta}}$ is estimated on-line using the modified EF RLS algorithm (Shin and Lee, 2020). The terms $\hat{B}_0\left(\mathbf{x}_0,\mathbf{u}_0\right)\Delta\mathbf{u}_{t-i}^{\sup}$ are responsible for the subtraction of contribution from the supporting signal to the flight dynamics (3) in order to obtain pure dynamics produced by the studied control surface.

6. SIMULATION RESULTS

In the current study a nonlinear model of the Boeing 747 aircraft is used to validate the designed approach. The Boeing 747 is a large transport aircraft with four wing-mounted engines. The aircraft has four ailerons, four elevators, two rudders, and four engines. We selected two different scenarios to demonstrate the operation of Aerodynamic and Actuator FDIs, namely, a single failure (hardover) and multiple failures with the presence of nonlinear dynamics in the elevator actuation system.

6.1 Single failure

Example of the proposed system operating in a failure case is demonstrated in Fig.3.

The considered case deals with a hardover of the inner left elevator. From the current simulation scenario, one can see the performance of the IBKS augmented with the TLF (TLF-IBKS). Performance of the plane IBKS is added for comparison purposes. On the upper subplot, one can see the evolution of the pitch angle. On the second subplot, one can see changes in the effectiveness of elevators. On the third subplot, the demanded control efforts are plotted. In the considered case the failure occurs at *t*=15 s. The TLF detects the failure at $t \approx 25$ s via testing hypothesis (10) and initiates the SLI. In the current case, the Actuator FDI is used. The TLF-IBKS algorithm estimates a new value for the elevator effectiveness after the failure and updates it in the control effectiveness matrix $\hat{B}_0$ used by the baseline controller.

As soon as a new value of effectiveness of the failed elevator is estimated, the system decreases the demand control efforts of this elevator. As a result of the TLF algorithm operation, a zero value is assigned to the element in the effectiveness matrix $\hat{B}_0$ corresponding to the failed actuator. From the upper subplot in Fig.3, one can see that TLF-IBKS has improved performance as compared to the IBKS, namely, it has decreased overshoots.

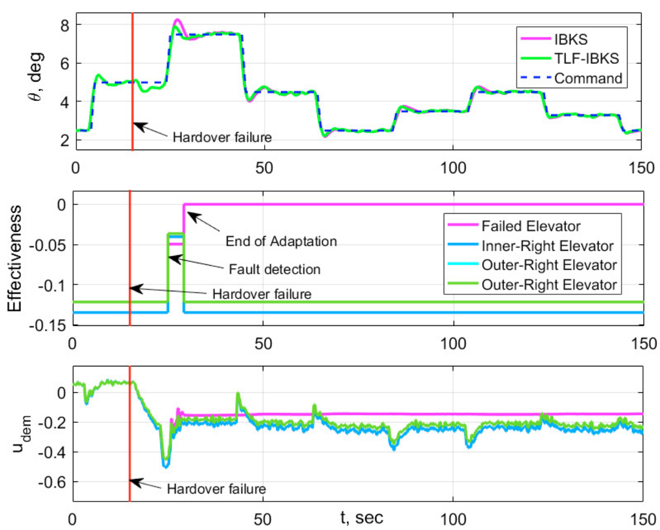

Fig.3. Algorithm performance in case of hardover

6.2 *Multiple failures and unmodeled actuator dynamics*

For some critical scenarios, for example, with multiple failures, the pure IBKS might become non-affine in control and precise estimations of control effectiveness matrix could help to tackle this issue.

The performance of the TLF-IBKS under multiple failures and the presence of an unmodeled actuator dynamics is considered in this section. Two actuators are simulated to be failed at the time moment t<0 sec, the identification of the effectiveness of that two stuck elevators was finished before *t*=0 sec. After that, an unmodeled second-order dynamics arises at *t* = 150 sec in one of the two working actuators: $F(s) = \left(2s^2 + s + 1\right)^{-1}$. Such type of dynamics could be a result of excitation of structural modes, control channel delay or their combination.

The simulation results are shown in Fig.4.

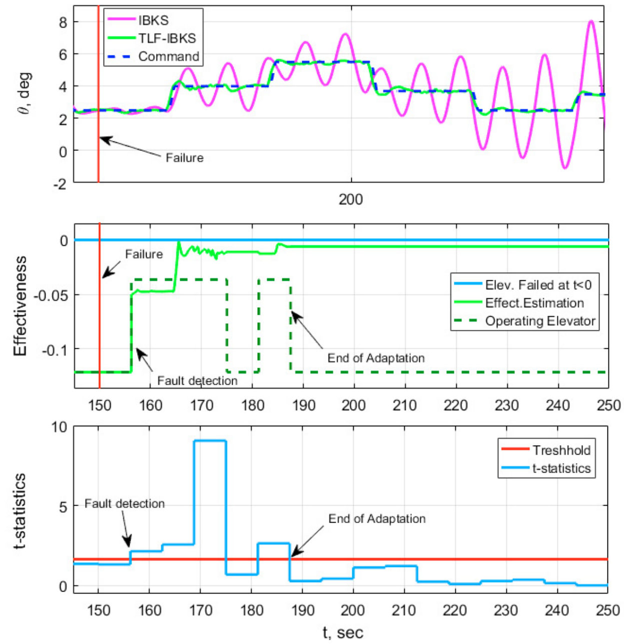

Fig.4. Performance of TLF-IBKS and IBKS controllers in case of unknown 2nd order actuator dynamics

On the top subplot of Fig.4, one can see the tracking performance of the controller, the performance of the IBKS is also provided for analysis. The effectiveness evolutions of four elevators are shown in the middle subplot and the bottom subplot shows the *T*-statistics.

After the unmodeled dynamics arose, the IBKS loses stability. On the contrary, the TLF-IBKS demonstrates stable behaviour, while achieving the expected level of performance. The uncertainty is detected via the generation of the innovation process, namely when the expected combined effectiveness value significantly differs from the estimated combined effectiveness value. In the current case the Aerodynamic FDI is used. The FLI initiates the SLI, and the estimation of effectiveness coefficient of the failed effector in the matrix $\hat{B}_0$ is updated on-line while the *T*-statistics is above the threshold value.

From the middle and bottom subplots one can see that the FLI is used as a governing process for the SLI. The SLI is initiated only when the T-statistics goes above the significance level. During the SLI a special control signal is formed, which can be seen in the middle subplot. In particular, the effectiveness of the operating elevator, which is responsible for the "supporting" signal, is artificially reduced, and when the innovation process is below the threshold value, the effectiveness of the operating elevator is brought back. When T-statistics goes below a significance level, the algorithm fixes the obtained value in $\hat{B}_0$, and FLI terminates the SLI. The other effect of the FLI could be observed in between the initiation and the termination of the SLI, namely, the identification is "paused" at $t \approx 175$ sec and $t \approx 194$ sec. At $t \approx 175-185$ sec and $t \approx 194-200$ sec there is no useful signal, because the aircraft does not perform identification manoeuvers, only noise measurements are available, so the FLI prevent the SLI from learning noisy data. It is well known that the EF RLS could suffer from the estimation windup when the persistent excitation condition is not achievable (Shin and Lee, 2020), so the FLI reduces the level of learned noise data and prevents SLI from the estimation windup.

7. CONCLUSIONS

IBKS is a control technique with a reduced dependency on the dynamics model. This approach uses estimates of the state derivatives and the current actuator states to linearize the dynamics with respect to current state. However, controller still requires knowledge of the control effectiveness, which might be crucial under possible failure. In this research, the Two-layer Framework for IBKS is proposed as an active FDI. At the first layer, the system performs on-line identification of the combined control effectiveness and detects possible anomalies via generation of the innovation process. Isolation of the faults is also performed at the first layer. The FLI, estimating the combined effectiveness, is used as a governing process for the SLI, determining the individual effectiveness of the failed control effectors. In case of possible failure, the FLI initiates the SLI for determination of individual effectiveness, and stops it when the error between the expected and estimated combined effectiveness is small enough. At the same time FLI acts as a filter that prevent SLI from learning noise data.

The other advantage of the TLF-IBKS is that it does not rely on assumptions or models of the aircraft dynamics under failure and, therefore, provides model-free FTC.

In severe conditions, with a combination of multiple failures and the presence of unmodeled actuator dynamics, the IBKS could become non-affine in control and lose the stability. Meanwhile, the proposed TLF-IBKS can tackle this issue, preventing from instability and providing required tracking performance.

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