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Two-Layer On-line Parameter Estimation for Adaptive Incremental Backstepping Flight Control for a Transport Aircraft in Uncertain Conditions

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Abstract: Presence of 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 two-layer parameter estimation procedure augmenting Incremental Backstepping (IBKS) control algorithm designed for a large transport aircraft. IBKS uses angular accelerations and current control deflections to reduce the dependency on the aircraft model. However, it requires knowledge of the control effectiveness. The proposed identification technique is capable to detect possible problems such as a failure or presence of unknown actuator dynamics even in case of redundancy of control actuation. At the first layer, the system performs monitoring of possible failures. If a problem in one of the control direction is detected the algorithm initiates the second-layer identification determining the individual effectiveness of the each control surface involved in this control direction. Analysis revealed a high robustness of the IBKS to actuator failures. However, in severe conditions with a combination of multiple failures and presence of unmodelled actuator dynamics IBKS could lost stability. Meanwhile, proposed control derivative estimation procedure augmenting the IBKS control helps to sustain stability.

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Keywords: On-line flight dynamics identification; Aircraft dynamics, control, guidance and navigation; Incremental Backstepping; Failures; Unmodelled dynamics.

1. INTRODUCTION

Enabling flight safety of passenger aviation in presence of 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 were 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, a great efforts have been undertaken to develop aircraft control design tools and techniques for enabling safe flight (Goman, Khramtsovsky and Kolesnikov, 2008; Smaili *et al.*, 2009; Ignatyev *et al.*, 2017; Ignatyev and Khrabrov, 2018; Abramov *et al.*, 2019). The idea that non-conventional control strategies can prevent possible accidents and recover aircraft from dangerous situations stimulates researches toward fault-tolerant and adaptive flight control (Chu *et al.*, 2009; Yucelen and Calise, 2012; Falconi, Marvakov and Holzapfel, 2016).

Gain-scheduling of linear feedback controllers is widely applied in commercial applications to achieve stabilization and satisfactory tracking performance of aircraft over a wide range of flight conditions. In case of severe and unpredicted changing in aircraft behaviour such controllers cannot be used or can be used only with a restricted functionality.

Nonlinear Dynamics Inversion (NDI) and Backstepping (BS) techniques have become popular control strategies for adaptation since they can be used for global linearization of the system dynamics and control decoupling (Slotine and Li, 1991). The BS control has advantages in comparison with the NDI, namely, it is more flexible and it is based on Lyapunov stability theory. Later, to make the BKS control more robust and fault-tolerant it has been formulated in an incremental-type sensor-based form (Sun *et al.*, 2013). However, even in this formulation controller still requires accurate knowledge of the control effectiveness. Additional adaptation strategies augmenting the BKS to reduce dependency on an aircraft model by on-line estimations of the control derivatives were applied for a high-performance aircraft model in (van Gils *et al.*, 2016).

One of the main challenges of an on-line identification is that the identification is carried out while a control system is operating (Klein and Morelli, 2006). It is common for an automatic control system to move several control surfaces in a proportional manner, bringing about nearly exact linear correlation between control surfaces. In addition, modern passenger aircrafts have many control effectors for both longitudinal and lateral control, so the multiple-input problem appears. Dedicated manoeuvres that maximise the observability of the parameters to be estimated, for example, individual elevator or aileron steps, cannot be carried out.

Reliable identification can be achieved via maximization of the information content in the data using proper excitations of

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the system. On the other hand, excessive system excitation because of ongoing manoeuvres can cause several undesired consequences, such as decrease of a passenger comfort or tracking performance. Thus the identification routine should be a trade-off between identification precision and performance requirements.

The present paper proposes a framework for the on-line identification of control derivatives augmenting IBKS control law, which was designed in (Cordeiro, Azinheira and Moutinho, 2019) for Boeing 747.

2. Incremental Backstepping

Sensor-based technique utilizing Incremental Dynamics (ID) is applied in (Cordeiro, Azinheira and Moutinho, 2019) to obtain an 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 two-layer on-line parameter estimation routine. Below, we will just provide a brief description of the this controller. Details could be found in the original paper.

2.1 Incremental dynamics model

A model representing an aircraft flight dynamics can be represented in the following form:

$$\dot{\mathbf{x}} = f_{\mathbf{x}}(\mathbf{x},\mathbf{u}), \qquad (1)$$

where the state vector $\mathbf{x}$ is composed by the airspeed V_t and the angular rate vector $\boldsymbol{\omega}$. The inputs $\mathbf{u}$ are the aircraft control surfaces and engines. Expanding (1) into the Taylor series around $(\mathbf{x}_0,\mathbf{u}_0)$ the dynamics (1) can be expressed in the following form

$$\dot{\mathbf{x}} \cong \dot{\mathbf{x}}_0 + \frac{\partial f_{\mathbf{x}}(\mathbf{x},\mathbf{u})}{\partial \mathbf{x}}(\mathbf{x}-\mathbf{x}_0) + \frac{\partial f_{\mathbf{x}}(\mathbf{x},\mathbf{u})}{\partial \mathbf{u}}(\mathbf{u}-\mathbf{u}_0). \qquad (2)$$

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

$$\Delta\dot{\mathbf{x}} \cong B_0\,\Delta\mathbf{u}, \qquad (3)$$

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

2.2 Cascaded Incremental Backstepping

The ID idea was used to design an IBKS controller. To increase the control 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.

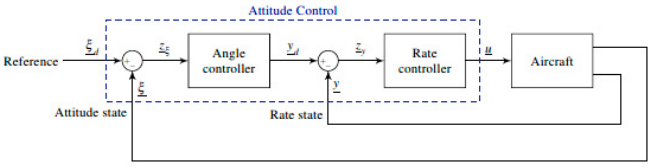


Fig.1. IBKS structure (courtesy of Cordeiro, Azinheira and Moutinho)

At the first stage, the knowledge of kinematics was preplaced by the measurements of the attitude state derivative $\dot{\boldsymbol{\xi}}_0$ to design an angle controller. At the second stage, the dynamics equations were partially replaced by evaluations of angular rate derivatives to design the second IBKS controller for the rate control. The desired angular rates $\mathbf{v}_\alpha$ were provided by the angle controller. The airspeed was introduced as a state to the second controller in order to design a rate controller which simultaneously tracks the airspeed and angular rates of the aircraft.

The final control law was designed to ensure the asymptotic convergence of the dynamics state $\mathbf{y} = \begin{bmatrix} V_t & \boldsymbol{\omega}^T \end{bmatrix}^T$ towards its desired value $\mathbf{y}_d = \begin{bmatrix} V_{td} & \mathbf{v}_\alpha^T \end{bmatrix}^T$. It has the following form:

$$\mathbf{u}_c = \mathbf{u}_0 + B_0^{-1}\Lambda\left(aC_{y\omega}^T T_\xi^T \mathbf{z}_\xi + W_y(\mathbf{y}_d - \mathbf{y}) + \dot{\mathbf{y}}_d - \dot{\mathbf{y}}_0\right). \qquad (6)$$

Here a is a design factor, $C_{y\omega} = \begin{bmatrix} \mathbf{0}_3 & \mathrm{I}_3 \end{bmatrix}$ is a selection matrix such as $\boldsymbol{\omega} = C_{y\omega}\mathbf{y}$, W_y is a design weight matrix, $\mathbf{z}_\xi = \boldsymbol{\xi}_d - \boldsymbol{\xi}$ is a kinematics error vector, $\boldsymbol{\xi}_d$ is a desired kinematics state vector. The matrix

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

relates the angular rate vector $\boldsymbol{\omega}$ with the attitude state vector.

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

To avoid infeasible commands provided by the controller, a Command Filter is added to the controller output. For incremental controllers, the CF is used to constrain the input in order to respect the actuators dynamics and saturation.

3. Two-layer identification routine

Recently several researches reported that IBKS demonstrates robustness to uncertainties and tolerance to faults (van Gils *et al.*, 2016; Jeon *et al.*, 2018; Cordeiro, Azinheira and Moutinho, 2019). Nevertheless, the IBKS still requires accurate knowledge of the control effectiveness. This paper introduces a two-layer identification framework detecting, isolating anomalies and estimating the aircraft control

derivatives when uncertainties are in the control actuation. These estimates are used for adjustment of the control effectiveness matrix B_0. A two-layer identification procedure is designed to find optimal solution between system excitation and performance. The general structure of the framework is given in Fig.2.

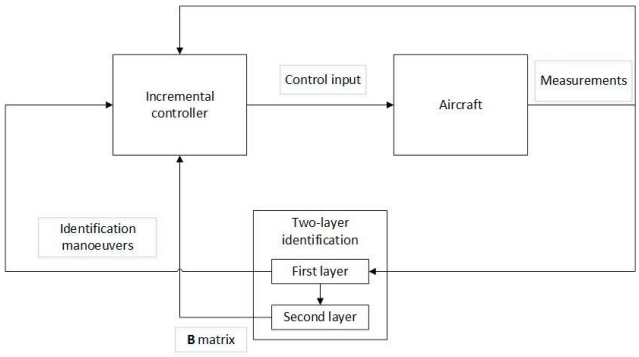


Fig. 2. Two-layer identification structure

3.1 On-line Identification Routine

Since an Aircraft Flight Control System (AFCS) sends the same signals for all individual control surfaces, the individual signals are proportional to each other. These cause a high-correlation between the individual signals. If all the input signal forms look the same, then any algorithm trying to assign values for the control effectiveness of each individual control will fail, because it is impossible to determine which of the multiple inputs, moved in the same manner, was responsible for the changes in the aerodynamic forces and moments. However, it is possible to estimate a combined control effectiveness, which essentially treats all of the correlated control surfaces as if they were a single control surface (Klein and Morelli, 2006).

At the first layer, the system performs monitoring of a combined effectiveness and possible failures via generation of an innovation process. The innovation process is defined as the difference between the estimated combined effectiveness and the expected combined effectiveness based on the model and the previous output data (Mehra and Peschon, 1971). 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.

The combined effectiveness could be used quite effectively for monitoring of the system states and for detection of a failure and it is used in the first layer of identification. However, it is impossible to distinguish which of the correlated control surface has a failure. In a case of failure of a single control surface we need to know an effectiveness of each control surface separately in order to implement more robust control. Thus, the failure should be localized. To solve this problem, modelling is done by introducing a priori information, fixing the effectiveness of all but one of the correlated control surfaces to a priori values.

3.2 Manoeuvres for Identification of Individual Control Surface Effectiveness

To increase the observability of the parameters, the individual control signal forms should be distinguishable. For this purpose, the control signals produced by the baseline controller is reshaped. In our case, we used an amplification matrix that decreases AFCS signals sent to all the control surfaces but one that under study. In such a case, a control signal is split into two signals, the first one is for a control surface which effectiveness is treated, while the second signal is for all other surfaces from the pool. Thus, the first signal is responsible for generating the required information for identification and second one is used for guaranteeing the aircraft stability.

4. Least-Squares On-line Identification

In the present section we would like to describe the approach for identification of the control effectiveness matrix B_0. The system dynamics could be represented in the form of incremental dynamics equation. Similar to (van Gils *et al.*, 2016) we assume that there is a vector $\boldsymbol{\theta}_j$ such that *j*-column of the B_0 could be represented as

$$\mathbf{b}_j = \boldsymbol{\Phi}_j^T(\mathbf{x},\mathbf{u})\,\boldsymbol{\theta}_j, j = n \tag{4}$$

where *n* is the number of the control surfaces. $\boldsymbol{\Phi}_j^T(\mathbf{x},\mathbf{u})$ is the regressor function, $\boldsymbol{\theta}_j$ is the unknown vector of parameters to be identified.

The system dynamics can be rewritten as

$$\Delta\dot{\mathbf{x}} \cong \left[\boldsymbol{\Phi}_1^T(\mathbf{x}_0,\mathbf{u}_0)\Delta\delta_1 \;\; \boldsymbol{\Phi}_2^T(\mathbf{x}_0,\mathbf{u}_0)\Delta\delta_2 \;\; \ldots \;\; \boldsymbol{\Phi}_n^T(\mathbf{x}_0,\mathbf{u}_0)\Delta\delta_n\right] \cdot\left[\theta_1 \;\; \theta_2 \;\; \ldots \;\; \theta_n\right]^T. \tag{5}$$

At the time *k* the following measurement equation can be introduced by using the past *N* measurements

$$\mathbf{y} \cong M\boldsymbol{\theta}^T, \tag{6}$$

where $\mathbf{y} = \left[\Delta\dot{x}_{k-N} \ldots \Delta\dot{x}_{k-1} \;\; \Delta\dot{x}_k\right]^T$ is the observed variable,

$$M = \begin{bmatrix} \Phi_1^T\left(\mathbf{x}_{k-N-1},\mathbf{u}_{k-N-1}\right)\Delta\delta_{1,k-N} & \ldots & \Phi_n^T\left(\mathbf{x}_{k-N-1},\mathbf{u}_{k-N-1}\right)\Delta\delta_{n,k-N} \\ & \ldots & \\ \Phi_1^T\left(\mathbf{x}_{k-1},\mathbf{u}_{k-1}\right)\Delta\delta_{1,k} & \ldots & \Phi_n^T\left(\mathbf{x}_{k-1},\mathbf{u}_{k-1}\right)\Delta\delta_{n,k} \end{bmatrix},$$

$\boldsymbol{\theta} = \left[\boldsymbol{\theta}_1^T\,\boldsymbol{\theta}_2^T \ldots \boldsymbol{\theta}_n^T\right]$ is the vector of unknown parameters. The unknown parameters $\boldsymbol{\theta}$ can be estimated on-line, for example, using the Recursive Linear Regression (RLS) algorithm with exponential forgetting.

4.1 First Layer of Identification

The first layer of identification is responsible for detection of a degradation in control effectiveness. For this purpose a combined effectiveness is used since degradation in any of the redundant control surfaces leads to degradation of the combined effectiveness.

In the present study the longitudinal motion of the Boeing 747 is considered. In this case a combined effectiveness of four sections of elevator working simultaneously are treated as if they are a single control surface. The identification of the combined control effectiveness is performed using the equation (6), where $\mathbf{y} = \left[\Delta\dot{q}_{t-N} \ldots \Delta\dot{q}_{t-1}\ \Delta\dot{q}_t\right]^T$ is the response variable vector, $\Delta\dot{q}_{t-N} \ldots \Delta\dot{q}_{t-1}\ \Delta\dot{q}_t$ is the pitch rate derivative record, $\mathbf{M} = \left[\Delta\delta_{1,t-N} \ldots \Delta\delta_{1,t-1}, \Delta\delta_{1,t}\right]$ is the predictor variable vector and $\boldsymbol{\theta} = C_{m_\delta}$ is the combined effectiveness of four elevators, which should be identified.

5.2 Second Layer of Identification

If the system detects any deviation from the nominal operational regime, the system steps into the second layer of identification where the failure is localized and the individual effectiveness is evaluated.

As it was mentioned before, identification of individual control effectiveness is complicated with a high-correlation between the individual signals. In order to tackle this problem, we use a priori information through fixing the effectiveness of all but one of the correlated control surfaces to a priori values.

While identifying the effectiveness of a certain elevator, the aircraft is demanded to perform pitching manoeuvers with reduced coefficients in the allocation matrix $W_s D_u$ for all control effectors responsible for the pitch control, except the coefficient relating to the elevator under study.

In this case the response variable vector is the following

$$\mathbf{y} = \left[\left(\Delta\dot{q}_{t-N}\right)_{res} \ldots \left(\Delta\dot{q}_{t-1}\right)_{res} \left(\Delta\dot{q}_t\right)_{res}\right]^T,$$

where $\left(\Delta\dot{q}_{t-i}\right)_{res} = \Delta\dot{q}_{t-i} - W_s D_u B_0\left(\mathbf{x}_0, \mathbf{u}_0\right)\Delta\mathbf{u}^{\sup}_{t-i}$, $i = 0 \ldots N$,

is the pure dynamics produced by a treated elevator section.

The predictor variable vector is based on a signal for control surface under study $\mathbf{M} = \left[\Delta\delta_{e_{ident}\,t-N} \ldots \Delta\delta_{e_{ident}\,t-1}\ \Delta\delta_{e_{ident}\,t}\right]$.

The identified parameter $\boldsymbol{\theta} = \left[C_{m_\delta}\right]_{ident}$ is the individual effectiveness of the control surface, W_s is the weight matrix required to produce the supporting control signal $\mathbf{u}^{\sup}$. Elements of W_s specify how supporting actuator signals differ from the base one. B_0 is the fixed effectiveness matrix defined prior to the identification. The terms $-W_s D_u B_0\left(\mathbf{x}_0, \mathbf{u}_0\right)\Delta\mathbf{u}^{\sup}_{t-i}$ are responsible for subtraction of contribution from the supporting signal to the flight dynamics in order to obtain a pure dynamics produced by the studied control surface. It should be noted that if W_s is too large the identification signal is not distinguishable from the supporting one. At the same time, if W_s is too small, the control authority is not enough to perform identification manoeuvres and guarantee the stability. Therefore, there is a trade-off between aggressiveness of identification manoeuvres, deduction of the all other control authorities W_s and stability during identification. In present study, we selected $W_s = 0.33$. This is motivated by the consideration that the effectiveness of all three supporting elevators should be not less than the studied elevator effectiveness. At the same time, for the values $W_s > 0.33$ the supporting signal is quite high and distorts the useful signal. Values of W_s that are less than 0.33 are not applicable from the stability point of view.

6. Fault Detection via Identification of an Innovation Process

The actual error signal from the system is tested against this hypothesis at a certain level of significance. In our case, the null hypothesis consists of testing the innovation processes for zero mean (Mehra and Peschon, 1971). More particularly, we used the Student's t-test (Anderson, 2003).

The t-statistics could be written in the following form

$$t = \left(\bar{X} - \mu\right) / \left((\sigma + b) / \sqrt{n}\right), \tag{7}$$

where $\bar{X}$ is the sample mean from a sample $X_1, X_2, \ldots, X_n$, of size n, σ is the (estimate of the) standard deviation of the data, and μ is the population mean. In our case X_i, is the estimated values of combined effectiveness. We also introduced a bias b in order to increase the tolerance of the detection procedure to "small" errors of the identification algorithm.

7. 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 actuation of it corresponds to four ailerons, four elevators, two rudders, and four engines.

The nominal condition from which the simulation starts is a straight flight towards North with 340 knot of True Airspeed and at an altitude of 5000 ft.

7.1 Single failure

Example of the proposed system operating in a failure case is demonstrated in Fig. 3. The purpose of the current example is just to demonstrate the operation of the two-layer identification procedure augmenting the IBKS. The

considered simulation case deals with a failure (stuck in position) of the inner left elevator. The algorithm performs identification of a new value for the elevator effectiveness using RLS and update it in the control effectiveness matrix B_0 used by the baseline controller. On the upper subplot one can see the results of the identification coplotted with the true effectiveness. On the second subplot one can see the steps performed by the system. On the third subplot the demanded control efforts are plotted. The bottom subplot demonstrates the innovation process generated by the system.

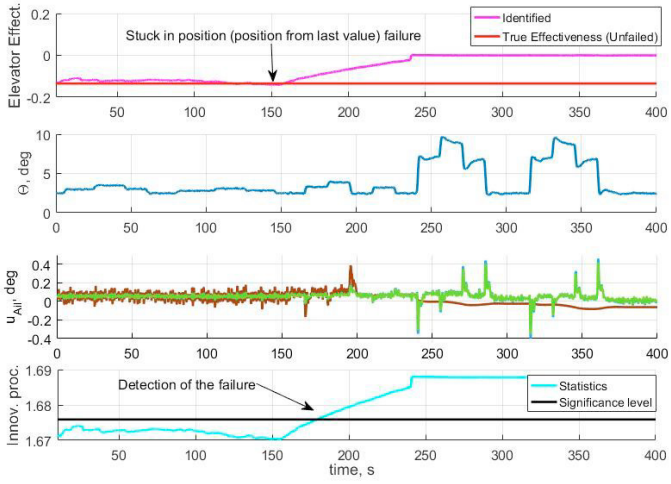


Fig. 3. Performance of the algorithm for individual elevator effectiveness on-line identification.

In the considered case the failure occurs at t=150 s. The failure is detected at $t \approx 175$ s via violation of the significance level of the innovation process statistics. After the failure being detected, the second layer of the identification procedure is initiated. While the effectiveness of the failed elevator is being updated, the system is decreasing the demand control efforts of this elevator.

7.2 Multiple failures and unmodelled dynamics

In order to check the performance of the controllers under the multiple failures and presence of unmodelled actuator dynamics we considered the following case. At the beginning, two actuators become failed at the time $t < 0$, namely, stuck-in-position of each is modelled. After that, an unmodelled second order dynamics arises at t = 80 s in one of the two working actuators (outer right elevator): $F(s) = \left(2s^2 + s + 1\right)^{-1}$.

The simulation results are shown in Fig.4. At the current case we considered that the identification of the effectiveness of failed elevators was performed before t=0 s. In this section, we are focused more on the effect of presence of unmodelled dynamics on the controller performance under multiple failures rather than on the detection of the failures, so we do not provide innovation process dynamics and the detection process itself. On the top left subplot of Fig.4 one can see a tracking performance of the controllers. Demonstrated on the right subplots are the angle-of-attack and pitch rate responses. Shown on the bottom left subplot are the effectiveness of the of the operating elevator and elevator subjected to the unmodelled dynamics. The effectiveness of the operating elevator is reduced during identification procedure as described above.

Starting from t=0 s, the adaptive IBKS uses updated values of effectiveness in B_0 matrix, corresponding to the two failed elevators. The results demonstrate that similar to the single failure case, there is small difference between responses of the adaptive IBKS and IBKS closed-loop systems from t = 0 s to t = 70 s, even in the case of double failure. This is because the IBKS reveals itself robustness to uncertainties due to incremental nature. However, after unmodelled dynamics arose, the IBKS closed-loop system reveals oscillatory behaviour in the response of the closed-loop system. On the contrary, the adaptive IBKS demonstrates stable behaviour, while achieving an expected level of performance. After detection of the uncertainty in the outer right elevator, adaptive IBKS starts the identification procedure. At the same time, the corresponding coefficient in

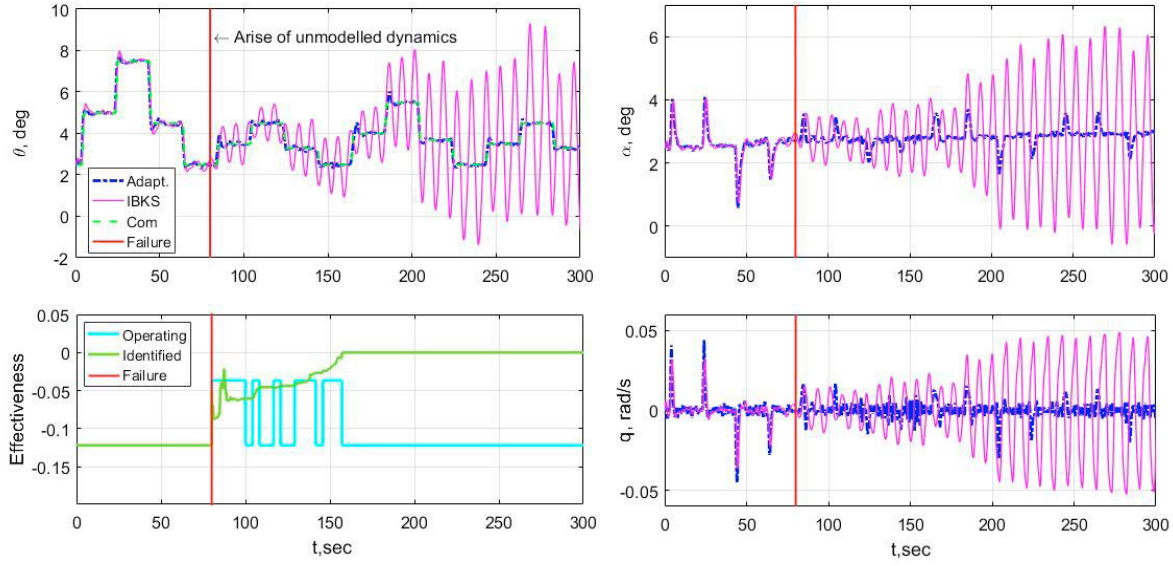


Fig. 4. Performance of the Adaptive IBKS and IBKS controllers

B_0 is updated according to the effectiveness evaluation. After the identification being finished, algorithm fixes the obtained value in B_0 (see bottom left subplot).

From the considered case one can conclude that IBKS tackles the piecewise-constant uncertainty in the control effectiveness quite efficiently, however in the case of unmodelled actuator dynamics, usage of the IBKS could be a tricky task.

Thus, in a case of severe uncertainty, which could be caused by multiple failures and presence of unmodelled actuator dynamics, on-line evaluations of the control effectiveness becomes vital.

6. CONCLUSIONS

Incremental Backstepping is recently developed technique with a reduced dependency on the on-board aircraft model. This approach uses estimates of the state derivatives and the current actuator states to linearize the flight dynamics with respect to current state. However, controller still requires knowledge of the control effectiveness. In this research Two-layer On-line Parameter Estimation for Adaptive Incremental Backstepping control, which is capable to detect possible problems, such as a failure or presence of unknown actuator dynamics, is proposed. At the first layer, the system performs monitoring of the combined control effectiveness and detects possible anomalies. If an anomaly is detected the algorithm initiates the second-layer identification determining the individual effectiveness of the each control surface involved in this control direction. Such structure requires less excitation of the system, thus, increasing comfort and tracking performance. In addition, fault isolation in the form of control effectiveness identification increases tolerance to faults since does not require information on a failure type and can be used for unforeseen failures.

Analysis revealed a robustness of the IBKS to actuator failures. However, in severe conditions with a combination of multiple failures and presence of unmodelled actuator dynamics, the IBKS lose stability. Meanwhile, proposed control derivative estimation procedure augmenting the IBKS control significantly improves the system performance.

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