ON-BOARD STATISTICAL DETECTION AND CONTROL OF ANOMALOUS PILOT-AIRCRAFT INTERACTIONS [1]

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Abstract: A statistical method for the on-board detection and control of oscillatory phenomena in pilot-aircraft systems is presented. Recursive identification is used to obtain a linear model of the system at every time instant. The estimated system parameters are monitored, and the system stability margins are continuously assessed. Oscillations due to stability loss are detected early, using a composite statistical hypothesis test. Finally, a simple stability augmentation system is designed to assist the pilot-aircraft system during the critical time intervals. The method is successfully tested with data from a detailed nonlinear aircraft model and a flight simulator facility.

Keywords: Recursive estimation, statistical analysis, decision making, aircraft control, critical damping, safety analysis, stability limits.

1. INTRODUCTION

"Aircraft Pilot Coupling" (APC) events are inadvertent aircraft attitude and flight path motions that result from anomalous interactions between the aircraft and the pilot (National Research Council, 1997). They occur under specific conditions when the combined dynamics of the aircraft and the pilot produce a marginally stable closed-loop pilot-aircraft system, and may lead to potentially severe aircraft damage or even destruction. Although it is very difficult to pinpoint the exact cause of specific APC events, the majority of them seem to result from deficiencies in the design of the aircraft and specifically of the flight control system (low rate limiting of actuators, flight controls or displays with excessive filtering and/or delay, and so on).

Traditional "rules of thumb" are used during the flight control design stage, followed by extensive testing under a variety of conditions. Nonetheless, even with such intensive design and testing, aircraft and/or pilot behavior may lead to adverse couplings with disastrous results. It would, therefore, be highly desirable to detect and correct potential symptoms of aircraft-pilot couplings *in flight*. Various schemes that attempt to explore this idea have been proposed.

Mitchell and Hoh (1999) proposed a scheme called ROVER (Real-time Oscillation VERifier) which

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checks for oscillatory signals in stick input and angular rate output and compares the characteristics of the two sets of signals. Cox and Lewis (1998) use neural network methods ("trained" with time-history data from actual adverse events) to identify oscillatory coupling phenomena. An approach based on a probabilistic neural network scheme has been developed by Raimbault and Fabre (2001). They classify flights as "incident-prone" and "incident-free" with respect to oscillatory behavior and the output of the detector is the probability of event occurrence. Jeram and Prasad (2003) propose a fuzzy logic based approach, with rules derived from oscillatory events expertise to identify such signals. Alternative approaches concentrate on factors such as the power spectral density of pilot input signals for the detection of oscillations (Hess and Stout, 1998), the behavioral changes of the human operator as a preamble to the occurrence of oscillatory phenomena (Repperger and Koivo, 1997) and special cases of pilot-aircraft couplings, such as limit cycle oscillations (Anderson, 1998).

The _aim_ of the present study is the introduction of a simple, yet effective means of early detection and control of adverse oscillatory phenomena. The proposed method uses:

(a) Recursive identification techniques to update, in flight, pilot-aircraft system models at every time instant. Model estimation is performed within a stochastic framework, accounting for sensor noise and the inherent uncertainties in the pilot-aircraft interaction. Unlike previous detection procedures, the proposed method does not require any expert knowledge during the tuning phase. The estimated models are used to monitor the pilot-aircraft damping factors throughout the flight, and to derive statistical limits for their values. The detection of stability loss (and the resulting oscillation onset) is accomplished via a composite statistical hypothesis test, allowing for rapid and reliable detection of incidents.

(b) A simple stability augmentation system, actuated as soon as oscillations are detected. This system is used to increase the damping of the pilot-aircraft loop and tame the oscillatory behavior during these instants of marginal stability.

2. ANOMALOUS INCIDENT DETECTION

2.1 The Monitor Design Method

The pilot-aircraft system is modelled via a discrete-time univariate ARMA (AutoRegressive Moving Average) model of the form [3]:

$$y[t] + \sum_{i=1}^{na} \alpha_i \; y[t-i] = e[t|\boldsymbol{\theta}] + \sum_{i=1}^{nc} c_i \; e[t-i|\boldsymbol{\theta}] \quad (1)$$

where t designates normalized discrete time ($t = 0, 1, \ldots$ with the corresponding analog time being $t \cdot T_s$, where T_s stands for the sampling period), $y[t]$ the monitored signal (system output), and $e[t]$ a zero-mean uncorrelated sequence (white) sequence (prediction error sequence) with variance σ_e^2. The AR and MA orders are designated as na and nc, respectively, while $\boldsymbol{\theta}$ represents the model parameter vector (AR/MA parameter vector). Notice that in the case of monitoring more than one signals a multivariate form of the model would be used (Fassois and Lee, 1993).

A recursive algorithm with forgetting factor is used for model parameter estimation, so that less weight is attributed to older (no longer representative) signal samples. Such an algorithm is well suited for tracing variations of the system's properties. Parameter estimation is carried out by minimizing the loss function:

$$V_t(\boldsymbol{\theta}) = \sum_{k=1}^{t} \lambda^{t-k} e^2[k] \quad (2)$$

at each time instant t. In this expression λ is the forgetting factor and $e[t]$ the current prediction error.

For the approximate minimization of the above criterion the well known Recursive Maximum Likelihood (RML) is used (Ljung, 1999).

2.2 Statistical Properties of the Damping Factor Estimates

Once a discrete-time estimated model is available at time instant t, its transfer function is used for obtaining the corresponding continuous-time poles and their damping factors and natural frequencies. These are continuously monitored throughout the flight. In addition, the computed statistical limits for the damping factors provide a measure of the accuracy of the estimated values. Given the covariance matrix $\boldsymbol{P}(\hat{\boldsymbol{\theta}})$ of the estimated model parameters, the global modal parameter [that is the model's natural frequencies and damping factors (Fassois, 2001)] covariance matrix may be obtained as follows.

Let a change of parametrization from a set of $m \times 1$ dimensional model parameter vector $\boldsymbol{\theta}$ to another set of physical parameters given in a $n \times 1$ dimensional vector $\boldsymbol{\kappa}$ (in this case the modal parameter vector) be designated by the non-linear functional relation:

$$\boldsymbol{\kappa} = f(\boldsymbol{\theta}) \quad (3)$$

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[3] Lower case/capital bold face symbols designate vector/matrix quantities, respectively.

Equation (3) is linearized using a first order generalized Taylor expansion at the current operating point $(\hat{\boldsymbol{\kappa}}[t], \hat{\boldsymbol{\theta}}[t])$, as follows[4]:

$$\begin{aligned} \boldsymbol{\kappa} &\cong \hat{\boldsymbol{\kappa}}[t] + \frac{\partial f(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\Big|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}[\boldsymbol{t}]}(\boldsymbol{\theta} - \hat{\boldsymbol{\theta}}[\boldsymbol{t}]) \\ &= \hat{\boldsymbol{\kappa}}[t] + \boldsymbol{J}(\hat{\boldsymbol{\theta}}[t])(\boldsymbol{\theta} - \hat{\boldsymbol{\theta}}[t]) \end{aligned} \tag{4}$$

where $\boldsymbol{J}(\hat{\boldsymbol{\theta}}[t])$ is the Jacobian matrix:

$$\boldsymbol{J}(\boldsymbol{\theta}) = \begin{bmatrix} \frac{\partial f_1(\boldsymbol{\theta})}{\partial \theta_1} & \frac{\partial f_1(\boldsymbol{\theta})}{\partial \theta_2} & \cdots & \frac{\partial f_1(\boldsymbol{\theta})}{\partial \theta_m} \\ \cdot & \cdot & \cdots & \cdot \\ \frac{\partial f_n(\boldsymbol{\theta})}{\partial \theta_1} & \frac{\partial f_n(\boldsymbol{\theta})}{\partial \theta_2} & \cdots & \frac{\partial f_n(\boldsymbol{\theta})}{\partial \theta_m} \end{bmatrix} \tag{5}$$

evaluated at the operating point $\hat{\boldsymbol{\theta}}[t]$. The deviation of the estimate $\hat{\boldsymbol{\kappa}}[t]$ from the true parameter vector $\boldsymbol{\kappa}_0$ is calculated from Equation (4) as:

$$\boldsymbol{\kappa}_0 - \hat{\boldsymbol{\kappa}}[t] \cong \boldsymbol{J}(\hat{\boldsymbol{\theta}}[\boldsymbol{t}])(\boldsymbol{\theta}_0 - \hat{\boldsymbol{\theta}}[t]) \tag{6}$$

Consequently, the covariance matrix of $\hat{\boldsymbol{\kappa}}[t]$ may be obtained as:

$$\begin{aligned} \boldsymbol{P}(\hat{\boldsymbol{\kappa}}[t]) &= E[(\boldsymbol{\kappa}_0 - \hat{\boldsymbol{\kappa}}[t])(\boldsymbol{\kappa}_0 - \hat{\boldsymbol{\kappa}}[t])^T] \\ &\cong \boldsymbol{J}(\hat{\boldsymbol{\theta}}[t])\boldsymbol{P}(\hat{\boldsymbol{\theta}}[t])\boldsymbol{J}^T(\hat{\boldsymbol{\theta}}[t]) \end{aligned} \tag{7}$$

The Jacobian matrix $\boldsymbol{J}(\boldsymbol{\theta})$ may be evaluated via a numerical differentiation scheme (the central difference approximation is presently used).

2.3 Statistical Decision Making

The detection of the adverse oscillatory phenomena may be formulated as a statistical hypothesis testing problem. For this purpose, the variable $\delta\hat{\zeta} = \hat{\zeta} - \zeta_0$ is considered, with $\hat{\zeta}$ being the damping factor estimated at each time instant and ζ_0 the threshold below which the system may enter an oscillatory phase. In the present case ζ_0 is set to zero. The following composite hypothesis testing problem is then considered for the true (but unknown) damping factor:

$$\begin{aligned} H_0 &: \delta\zeta > 0 \ \text{(damped system)} \\ H_1 &: \delta\zeta \le 0 \ \text{(undamped system)} \end{aligned} \tag{8}$$

In the above, H_0 and H_1 designate the null and alternative hypothesis, respectively. Treating the computed variance of $\hat{\zeta}$ as a fixed quantity, the following test (characterized by a maximum risk of α, that is maximum probability of accepting H_1 when H_0 is true equal to α) is used:

$$\begin{aligned} \frac{\delta\hat{\zeta}}{\sqrt{\delta\sigma^2}} > Z_\alpha &\Longrightarrow H_0 \text{ is accepted} \\ Else \quad &\Longrightarrow H_1 \text{ is accepted} \end{aligned} \tag{9}$$

[4] The hat over a quantity designates estimator/estimate.

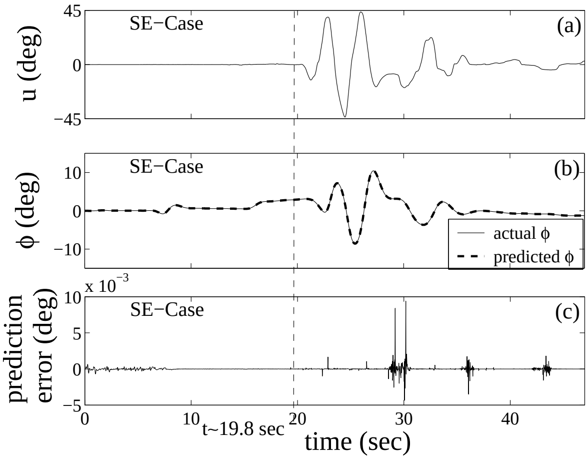

Fig. 1. SE-Case time histories: (a) Pilot input $u(t)$, (b) actual roll attitude $\phi(t)$ versus ARMA$(10, 0)$ model-based predictions, (c) model-based prediction error (the vertical dashed line designates APC detection).

with $\delta\sigma^2$ designating the variance of $\delta\hat{\zeta}$ (which is equal to that of $\hat{\zeta}$) and Z_α the standard normal distribution's α critical point. A typical value for α is 0.05, for which $Z_{0.05} = -1.645$.

2.4 Application to APC Incidents

The monitor design method is applied to two particular anomalous pilot-aircraft interaction cases. The roll data of the first case (Figure 1) have been generated using a detailed non-linear aircraft model (Ciniglio and Verse, 1999), (Samara, *et al.*, 2003). Note that the recorded roll attitude (sampling frequency of 50 Hz) has been based upon actual pilot input data, covering a time period of approximately 47 seconds. The oscillations are present from $t = 15\,sec$ onward, start growing at $t = 17$ sec, and become quite severe from $t \approx 19.80$ to $t \approx 35$ sec. The roll attitude attains values between $+10.5$ deg and -8.6 deg. This first case is referred to as the SE-Case.

The second set of data is flight recordings obtained from the NLR Simulator Facility in Amsterdam (The Netherlands). This case is referred to as the Simulator Case. The specific flight examined exhibits adverse APC events on the roll axis (Figure 2), which occurred during the ADFCS-II research project simulator campaign. The data record covers a time interval of approximately 148 sec and is recorded at 50 Hz. Oscillations start from $t = 122$ sec and reach extreme roll attitudes of approximately $+6.7$ deg and -5.4 deg.

Stochastic Modelling
The roll attitude, ϕ, is chosen as the signal $y[t]$ of the pilot-aircraft system to be modelled. The selection of the $ARMA(n_a, n_c)$ model orders and the forgetting factor λ reflect the tradeoff between

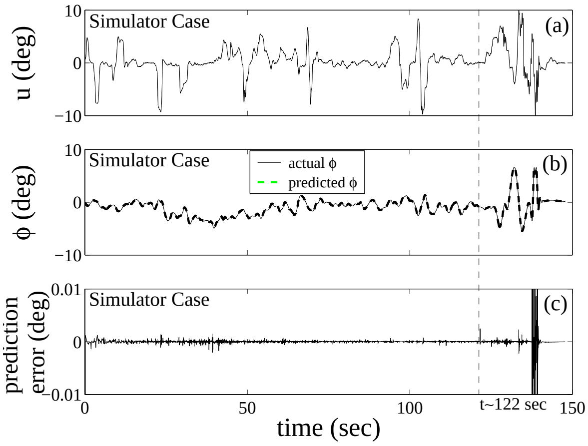

Fig. 2. Simulator Case time histories: (a) Pilot input $u(t)$, (b) actual roll attitude $\phi(t)$ versus ARMA$(10, 0)$ model-based predictions, (c) model-based prediction error (the vertical dashed line designates APC detection).

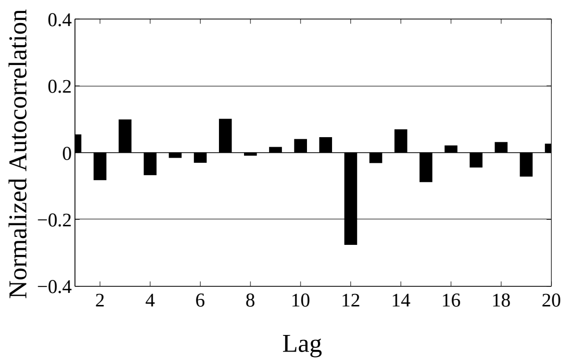

Fig. 3. Sample normalized autocorrelation of the model residual sequence (Simulator Case; "local" autocorrelation within a signal window).

low Residual Sum of Squares (RSS) and easy real-time application. A rigorous selection of both (n_a, n_c) and λ implies that the values of $e[t]$ in Equation (1) should form a white sequence, while a low RSS must be achieved. Extensive tests, with $n_a \in [2, ..., 25]$, $n_c \in [0, ..., 25]$ and $\lambda \in [0.975,\ 1)$, have shown that high order models are quite satisfactory with respect to the previous constraints. However, such models are quite cumbersome for on-line use. For that purpose, a lower order model with $n_a = 10$, $n_c = 0$ and $\lambda = 0.99$ proves sufficient in describing the most important system dynamics, i.e. the damping factor corresponding to dangerous APC frequencies (up to 2 Hz). At the same time, low RSS values are obtained, with $e[t]$ forming an almost uncorrelated sequence for $t \geq 10$ sec (SE-Case) and $t \in [10, 128]$ sec (Simulator Case). Furthermore, inside the above mentioned intervals the obtained residuals are locally uncorrelated in the majority of the cases (see Figure 3).

The one-step-ahead predictions of the recursive ARMA$(10, 0)$ model are compared to the actual roll attitude signal ϕ in Figures 1(b,c) and 2(b,c) for the SE and the Simulator Cases, respectively. In both cases, the prediction errors (model residuals) are substantially constrained, since the actual and predicted signals practically coincide.

Remark: To compensate for the lack of *initial conditions* for $\hat{\boldsymbol{\theta}}[t]$ and its "covariance" matrix $\boldsymbol{P}[t]$, the values of $y[t]$ corresponding to the (analog) time interval $[0,\ t_i]$ sec are used to perform:
i) one forward pass (i.e. a normal operation of the algorithm up to time t_i),
ii) one backward pass (i.e. a reprocessing of the signal data recorded from t_i to 0 using as starting point for $\hat{\boldsymbol{\theta}}$, $\boldsymbol{P}$ the final values $\hat{\boldsymbol{\theta}}[t_i]$, $\boldsymbol{P}[t_i]$ of the forward pass), and,
iii) one final forward pass up to t_i.
The obtained values for $\hat{\boldsymbol{\theta}}[t]$ and $\boldsymbol{P}[t]$ after these passes improve the performance of the recursive algorithm, at the expense of having the monitoring method inoperative during the first (arbitrarily chosen) t_i sec.

APC Detection
As indicated in Figures 4 and 5 for the SE and Simulator cases, respectively, the ARMA$(10, 0)$ damping factor (corresponding to frequencies up to 2 Hz) is capable of tracing the aircraft-pilot oscillations onset very quickly. Indeed, the damping reaches near-zero values around $t \sim 16$ sec for the SE-Case and $t \sim 122$ sec for the Simulator Case. The onset of oscillations is formally detected by the composite hypothesis testing procedure of Equation (9). This is illustrated in the bottom parts of the figures, where the evolution of the test statistic $\delta\hat{\zeta}/\sqrt{\delta\sigma^2}$ is presented. The test statistic becomes smaller than the threshold $Z_\alpha = -1.645$ at $t = 19.32$ sec for the SE-Case and $t = 121.6$ sec for the Simulator Case; hence high amplitude oscillations are detected (the H_0 hypothesis is rejected at these instants).

3. ANOMALOUS INCIDENT CONTROL

Once the beginning of an APC incident is detected, a properly designed stability augmentation system may be used to provide the necessary extra damping. A simple solution to this effect is to include a PD or phase-lead controller in the pilot aircraft loop (Cook, 1997).

This approach is presently followed, as it has been confirmed (via the estimated models) that there exists a dominant pair of poles to which the oscillations may be effectively attributed. At the time intervals that adverse oscillations are observed, this pair is either marginally stable or unstable. Therefore, a properly designed PD controller may substantially augment the stability margins by

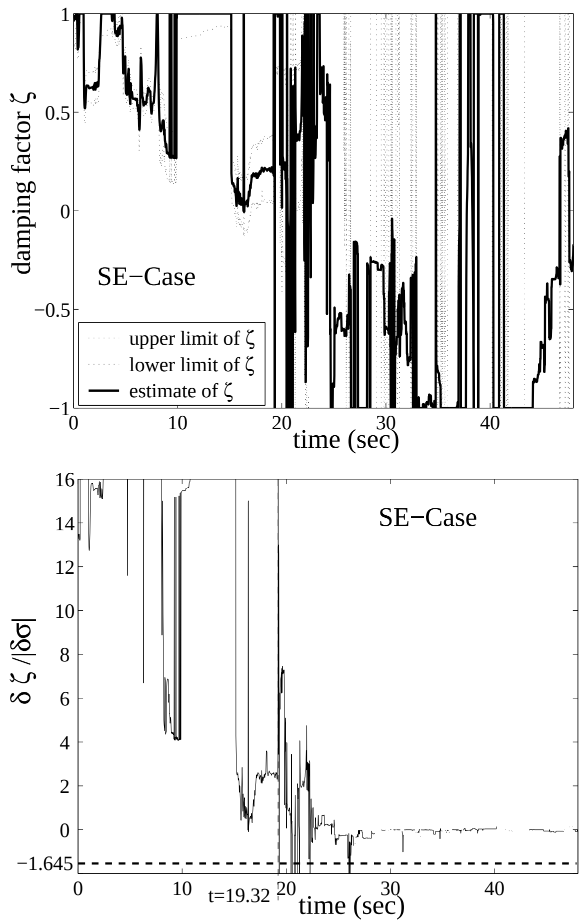

Fig. 4. SE-Case recursive $\mathrm{ARMA}(10,0)$ based damping factor and interval estimates (top) and composite hypothesis test for the detection of oscillations (bottom) [the horizontal dashed line designates the limit below which an APC incident is detected; the vertical dashed line designates the APC detection time].

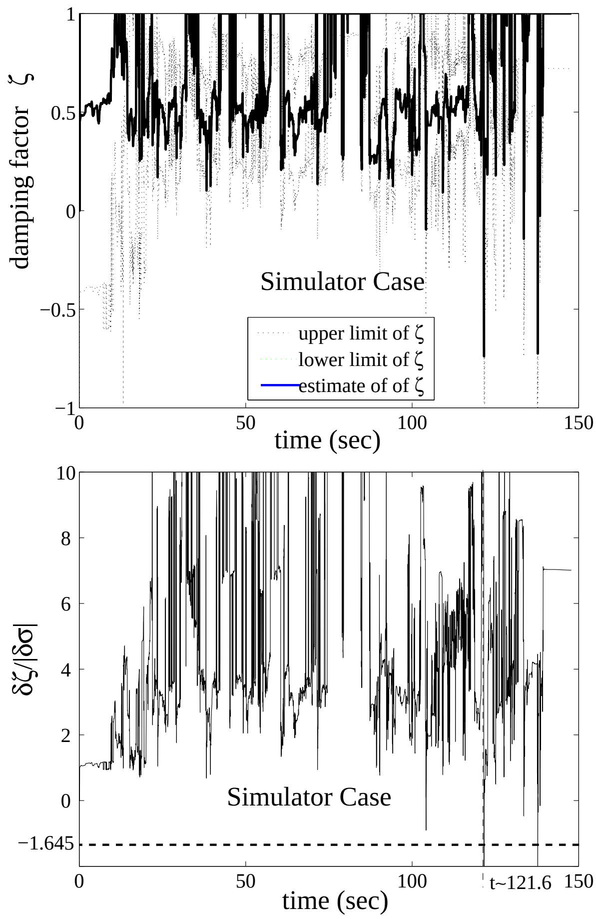

Fig. 5. Simulator Case recursive $\mathrm{ARMA}(10,0)$ based damping factor and interval estimates (top) and composite hypothesis test for the detection of oscillations (bottom) [the horizontal dashed line designates the limit below which an APC incident is detected; the vertical dashed line designates the APC detection time].

"pushing" this set of poles to the left on the complex plane. Note that since the augmentation device affects solely the pilot input (i.e. modifies the actual input fed to the aircraft – see the top part of Figure 6), the aircraft characteristics (saturation limits, rate limiters etc) remain unaltered.

The stability augmentation system is designed as an inner feedback loop, with the PD controller activated only during the critical time periods where the pilot-aircraft system stability is marginal. In the SE-Case presently considered, this period is for $t \in [19.32, 35]$ *sec*. The selected continuous-time PD controller transfer function is $C(s) = K_p \frac{s}{1+T_D s}$, with $K_p = 2000$ and $T_D = 0.01$. The closed-loop system is indicated in Figure 6 (top), while its effectiveness is illustrated through a comparison of the two roll attitudes: that of the system using stability augmentation and that of the standard (unaugmented) system (bottom part of the figure).

During the critical time intervals, the actual input $u^*(t)$ fed into the aircraft thus is:

$$u^*(t) = u(t) - K_p \cdot \frac{s}{1+T_D s} \cdot \phi(t) \qquad (10)$$

instead of the actual pilot input $u(t)$. Note that once the oscillations are over, the feedback is *gradually* reduced to zero, thus avoiding abrupt system transitions. The beneficial effects of using this simple system are quite clear. The oscillations have almost disappeared, while the general form of the two roll signals is similar. Furthermore, the entire procedure of oscillations statistical detection and stability augmentation is rapid and easy to implement.

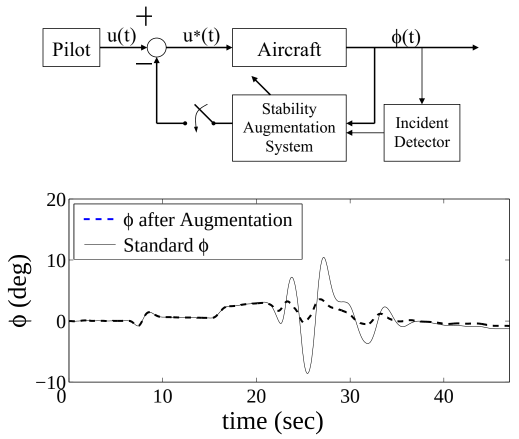

Fig. 6. Schematic diagram of the stability augmentation system (top), and comparison of the unaugmented and augmented system responses (bottom; SE-Case).

4. CONCLUSIONS

A method for the on-board detection and control of undesirable pilot–aircraft interactions has been introduced. The stochastic modelling framework employed accounts for inherent uncertainties in the measured signals and the pilot-aircraft interaction. Unlike previous detection procedures, the proposed design does not require expert knowledge for its tuning.

The detection of low system stability margins is based upon monitoring of the system damping factors via recursively estimated linear models. Statistical limits for the damping factor values are established, and potential oscillations are formally detected via a statistical composite hypothesis test. Finally, a simple stability augmentation system, which provides extra damping during the critical periods of marginal pilot–aircraft system stability, is used for oscillation suppression. Simulation tests, carried out using flight data from a flight simulator facility and a highly non-linear aircraft model, have indicated that the method is effective, and that the detection of stability loss preceding the onset of oscillations is both rapid and reliable.

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