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A Data-Driven Approach to Detect Faults in the Airbus Flight Control System

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Abstract: This paper presents a data-driven strategy for the detection of failures impacting the flight control system. Early and robust detection of Oscillatory Failure Case (OFC) allows the aircraft structural design to be optimized, which in turn helps improve the aircraft environmental footprint thanks to weight saving. Compared to existing model-based techniques already used on in-service Airbus aircraft, this paper studies a novel signal processing approach based on distance and correlation. It is shown that a mixed similarity index between Euclidean distance and logarithmic invariant divergence gives promising detection results. This paper details the proposed approach by insisting on practical constraints due to implementation in embedded real-time systems such as the flight control computer. Preliminary results obtained from a Verification & Validation (V&V) on-going campaign are presented.

Keywords: Aircraft, Flight Control, Fault Detection and Diagnosis, Oscillatory Fault Case

1. INTRODUCTION

The Electrical Flight Control System (EFCS, a.k.a. Fly-By-Wire – FBW) for large civil aircraft has established an industrial standard for modern 4th generation aircraft. Its main advantages include sophisticated control of the aircraft, flight envelope protection functions, pilot workload alleviation and weight saving [1]. For future aircraft, one of the challenges identified by the aeronautic sector is to achieve the long term goals of greener aviation [2]. In particular, even if it is not obvious at first sight, early and robust detection of EFCS faults that may have an influence on structural loads contribute to the overall optimization of aircraft structural design and thus contribute to weight saving. This is in line with the said sustainability objectives as e.g. less weight means less fuel consumption. So, the ability to detect these faults on time and at the required level is of primary interest when designing EFCS. This can be translated into investigating and developing appropriate Fault Detection and Isolation (FDI) techniques (called monitoring) to guarantee compliance with the environmentally-friendlier objectives. The main EFCS-failure cases of interest are: (i) Runaway (a.k.a. hard-over): an unwanted deflection of the control surface that can go until its stops if not detected; (ii) Jamming (a.k.a. lock-in-place): the control surface is stuck at its current position and it is no longer possible to control it correctly; (iii) Oscillatory Failure Case (OFC): a spurious sinusoidal signal propagates through the control loop and leads to an unwanted oscillation of the control surface. This is the fault case of interest addressed in this paper.

The industrial FDI state-of-practice used by all aircraft manufacturers to detect EFCS faults is to provide high levels of hardware redundancy in order to perform consistency tests, cross checks and built-in-tests of various sophistication [1]. This current approach fits well in the certification process and eases the design and analysis of the system. But to achieve more stringent objectives, i.e., to detect earlier smaller fault amplitudes, which in turn helps improve the aircraft environmental footprint, it is required to move from these present-day approaches to more advanced techniques. Model-based strategies have been significantly investigated in the past decade [3][4]. To the best of the authors' knowledge, signal processing strategies have been rarely investigated [5]. This paper proposes to consider data-driven approaches to detect OFC in EFCS, based on signal processing methods using signal distances and correlations.

This paper is organized as follows: Section 2 gives more details on OFC root cause and FDI requirements. Section 3 is devoted to model-based approaches dedicated to OFC detection. It also provides the main reasons to move toward signal processing techniques. Section 4 is dedicated to the proposed data-driven approaches. Section 5 deals with V&V activities performed to assess the robustness and performances of the proposed technique. Some concluding remarks and perspectives are finally reported in Section 6.

2. OFC CONTEXT AND FDI REQUIREMENTS

A typical Airbus Flight Control Computer (FCC) architecture is depicted in Figure 1. It consists of a dual channel scheme where the so-called "COM" (command) channel is dedicated mainly to the flight control law computation and to the control surface servo-loop. The so-called "MON" channel (monitoring) is primarily dedicated to the monitoring of all EFCS components. An OFC is an unwanted oscillating signal propagating within the control loop. It mostly comes from an electrical component in fault mode or is due to the breaking of a mechanical element. These fault sources are located between the FCC and the control surface, including these two elements. OFC signals are considered as sinusoidal signals with frequency uniformly distributed over a low frequency range (generally lower than 15 Hz). Their amplitudes are uniformly distributed. Beyond the upper frequency, OFCs have no

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significant effects because of the actuator low-pass behaviour. For structure-related system objectives, it is necessary to detect OFC beyond a given amplitude *X* in a given number of periods *Y*, for any OFC frequency. The detection time is expressed in period numbers, which means that, depending on the unknown failure frequency, the time really allowed for detection is not the same. Two kinds of OFCs have to be considered, namely "liquid" and "solid" failures. The liquid failure adds to the normal signal (inside the control loop) while the solid failure substitutes the normal signal (Figure 2). The OFC detection methodology must take into account the specificities of these two different cases.

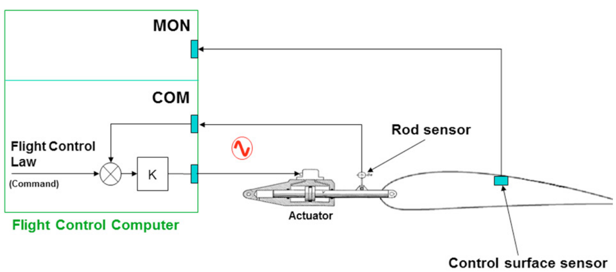

Figure 1: The Airbus COM/MON FCC architecture.

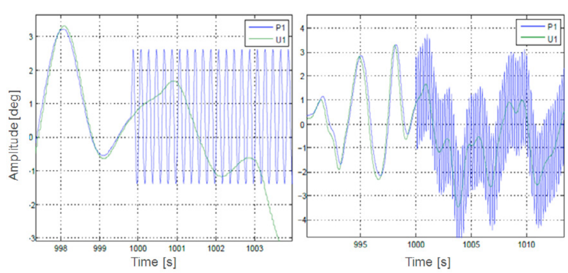

Figure 2: Solid (left) and liquid OFC (right) from t=1000s. U1 is the command signal, P1 is the control surface position.

To understand the link between OFC FDI and the aircraft weight saving, it should be noticed that an aircraft is a flexible body that has been sized to withstand a given load envelope. This is done by taking into account the effects of manoeuvers, wind gusts, turbulence and system faults during the aircraft design. If a small amplitude OFC occurs, an additional load is locally generated inside the design load envelope (green point in Figure 3). In this case, it is not required to dedicate FDI for this fault. However if an OFC with higher amplitude arises then the associated load can lie outside the design envelope (red point in Figure 3). It is then required to detect the fault quickly, before the load reaches a too high level. So, there is clearly a link between the minimum detectable amplitude and loads. More precisely, if a failure of a given amplitude cannot be detected, this amplitude must be considered for load computations. The result of this computation can lead to reinforce the structure, which de facto means increasing the aircraft weight. In order to avoid reinforcing the structure and consequently to save weight, low amplitude failure must be detected early enough.

Before the A380, Airbus aircraft are using basic signal processing techniques to detect OFCs. These solutions have been successfully validated and certified and provide a complete OFC coverage without false alarm in the EFCS.

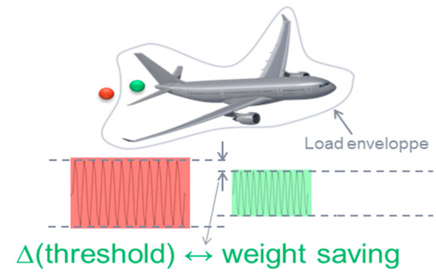

Figure 3: The red point shows a local augmentation of the structural load due to an OFC of too high amplitude.

3. MODEL-BASED APPROACHES

Primarily because of the use of new generation actuators and due to more stringent load requirements, it was not possible to equip the A380 with legacy OFC detection strategies. A basic model-based approach was developed to cover OFC detection on all primary control surfaces (ailerons, elevators and rudders) [6]. This analytical redundancy technique produces a fault indicator defined as the difference between the measured control surface position and an estimated position. A nonlinear hydraulic actuator model is used to estimate the position. In order to reduce the computational burden, some model parameters are fixed to their most probable value (e.g., hydraulic pressure, actuator damping coefficient, etc.). The decision making step consists of detecting the OFC signal within several spectral subbands by counting successive and alternate crossings of a given threshold (i.e., the fault amplitude to detect). This strategy is currently used on-board in-service A380. It provides full OFC detection coverage with very good robustness.

In order to improve this elementary model-based approach and to be compliant with more stringent load requirements (as well as a dedicated EFCS architecture), a joint parameter and state estimation technique has been developed on the A350 [7]. The online physical parameter estimation of the actuator model allows for parameter variations during aircraft flight and de facto improves the model accuracy. The estimation is done thanks to a modified version of an extended Kalman filter. A decision making-step similar to the one used in the A380 is kept. The whole strategy permits smaller fault amplitudes to be detected earlier.

These model-based techniques have been primarily investigated in particular because models were already available for other purposes (e.g. simulator development). They have proved their efficiency, viability and maturity through in-service use and have received certification on new generation Airbus A380 and A350 aircraft.

However, these approaches are still suffering from some drawbacks. Model-based residuals are always sensitive to modelling errors. A lot of techniques have been developed to compensate for these errors ([8] and references therein). But their performance often implies a complexity not compliant with real-time constraints. A strong modelling effort is also needed to get a model whose accuracy is compatible with good detection performance and reduced computational complexity. Several kinds of actuators are now used on-board a modern civil aircraft, such as the hydraulic conventional actuator or the Electro-Hydrostatic Actuator. It means that a model is needed for each actuator type which limits the genericity of model-based approaches. Indeed, from an industrial point of view it is better to use the same strategy in different contexts (i.e., different actuators or control surfaces). The high-level parameter tuning of the monitoring is also a key point for an industrial use. The simple model-based approach used in the A380 is an open-loop strategy (only the system command is used) which does not require a complex tuning. The A350 technique is a closed-loop scheme (in the sense that both command and position are injected in the model) which is tricky to tune. Indeed, the position used in the model can be polluted by OFC while the command can normally oscillate (e.g., in response to atmospheric turbulence). Consequently, the FDI filter should be correctly tuned to take into account these two antagonist situations (normal/abnormal oscillation). Motivated by these remarks, it has been decided to investigate signal processing methods that are not model-based. One of the key drivers is to reduce the number of hypotheses on the system, which in turn will help all industrial constraints to be accounted.

4. A DATA-DRIVEN APPROACH

The problem of detecting oscillations embedded in noise is very common in many fields (see, e.g., [9][10]), and many approaches are good candidates. However, industrial constraints must be taken into account, especially in FBW systems: e.g. very low false alarm and missed detection probabilities, low complexity, low execution time, genericity and high-level tuning. Among all potential signal processing techniques it has been decided to focus on distance and correlation-based methods that satisfy these industrial constraints. One can indeed observe that in a nominal situation (Figure 4) command and position signals are very similar. The phase difference between both signals is called the “drag error” and represents the time physically needed by the actuator to move. Some transient differences can be observed in the amplitude of both signals especially in case of strong aerodynamic forces. However, in presence of OFC, a loss of correlation or distance occurs and shows a clear difference between command and position. At high frequency, the aircraft does not react to OFC as the flight control laws are not designed to control high frequencies. At low frequencies, OFC impacts the aircraft behaviour and the control law tends to compensate for the fault (Figure 5).

The proposed strategy is based on the estimation of the agreement level between command and position. It consists of generating an error signal d, which is compared to a fixed or adaptive threshold $\alpha(t)$. If d is greater than the threshold during a given time interval, a fault is detected. The simplest solution for comparing two signals x (e.g., U1) and y (e.g., P1) is to compute the Euclidean Distance (ED) over a sliding window of length N:

$$d(x, y) = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2} \tag{1}$$

However, this distance is not robust enough in case of transient errors due to aerodynamic forces or in case of too high drag errors during dynamic manoeuvers. The Complex Invariant Distance (CID), proposed in [11], is an attempt to define a more robust similarity measure, which compares two signals by resorting to a measure of their global complexity. It consists of weighting the ED by a dedicated factor to produce an index of agreement, which was intended to be invariant with respect to (w.r.t.) the complexity:

$$CID = c_f d(x, y) = \left(\frac{\max(CE(x), CE(y))}{\min(CE(x), CE(y))} \right) d(x, y) \tag{2}$$

where c_f is a correction factor defined thanks to:

$$CE(x) = \sqrt{\sum_{i=1}^{N-1} (x_i - x_{i+1})^2} \tag{3}$$

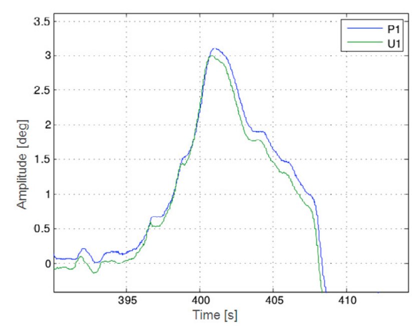

Figure 4: Similarity between command U1 and position P1 in a fault-free situation (real flight test data).

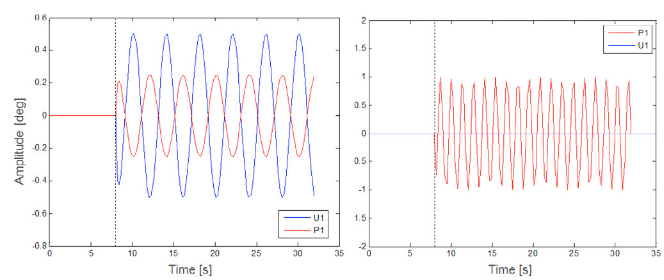

Figure 5: Loss of similarity in case of OFC occurring at t=8s. Left: low frequency, right: high frequency. U1 is the command signal and P1 is the control surface position.

The definition of CID is intuitively motivated by the fact that if we could "stretch" a time series until it becomes a straight line, a complex time series would result in a longer line than a simple time series. Comparing the stretched versions of two time series allows their similarity to be quantified. In other words, the CID measures a quantity similar to the ratio of the curvilinear distances of the two considered signals. It is interesting to note that the c_f factor involves a first order derivative and thus that CID can be seen as an agreement index between the derivative of x and y. However c_f is not a correlation coefficient and is “only” related to the dynamic similarity. For instance, two sinusoidal signals with the same parameters except that they are fully phase shifted (180°) have a temporal correlation coefficient equal to -1 and a c_f factor equal to 1. Finally, it is interesting to note that despite its name, CID is not a distance as it does not respect the full triangular inequality but only a relaxed form. A way to bypass the CID drawbacks is to extend the concept of similarity between the numerical values of x and y, e.g., by including a dynamic similarity measured through correlation coefficients. This can be done by defining the following similarity measure depending on a tuning parameter K [12]:

$$d_s(x,y) = \frac{2}{1+e^{KC_{xy}}} d(x,y) \tag{4}$$

where C_{xy} is a correlation coefficient adapted to measure the similarity in terms of dynamic by emphasizing the slope and the sign of two signals:

$$C_{xy} = \frac{\sum_{i=1}^{N}(x_{i+1}-x_i)(y_{i+1}-y_i)}{\sqrt{\sum_{i=1}^{N}(x_{i+1}-x_i)^2(y_{i+1}-y_i)^2}} \tag{5}$$

and K allows a trade-off between the temporal and dynamical properties of x and y. The two previous measurements of similarities between time series are not distances but rather divergences. As a contribution to this research field, we propose to define a new similarity measure that is more adapted to the OFC context and industrial constraints. This measure will be used in a threshold-based logic to detect OFC according to industrial requirements. First of all, the control surface position in the fault free case $y(t)$ is modelled by a positive affine dilatation of the command $x(t) \in L_2$:

$$\begin{aligned} &y(t) = \lambda x(\alpha t + \tau) + \mu \\ &\lambda > 0, \mu \in \mathrm{R}, \alpha > 0, \tau \in \mathrm{R} \end{aligned} \tag{6}$$

Indeed, there are multiple varying parameters explaining the differences between command and position in a fault-free situation, such as the signal expansion/contraction λ (due, e.g., to aerodynamic forces), the delay τ (drag error), the offset μ and the time expansion or contraction α (e.g., due to FCC asynchronism between COM and MON channels). Therefore, a meaningful objective is to define a similarity measure (divergence) $D(x\|y)$ invariant w.r.t. the aforementioned varying parameters and that verifies:

$$\forall x(t), y(t) \in L_2 : D(x\|y) \geq 0, D(x\|y) = D(y\|x)$$
$$\mu \in \mathrm{R}, \alpha > 0, \tau \in \mathrm{R} : D(x(t)\|\lambda x(\alpha t + \tau) + \mu) = 0 \Leftrightarrow \lambda \geq 0 \tag{7}$$

In other words, we are looking for a symmetric divergence that must be equal to 0 in the fault-free case (i.e., when the position is a positive affine dilation, with $\lambda \geq 0$).

Assuming that the mean E and the variance V of a signal $x(t)$ are finite and have:

$$E\left[x(t)\right] = \lim_{T\to\infty} E_T\left[x(t)\right], \quad V\left[x(t)\right] = \lim_{T\to\infty} V_T\left[x(t)\right]. \tag{8}$$

where $E_T[x(t)]$ and $V_T[x(t)]$ are the mean and variance computed on the interval $[-T/2;T/2]$.

A possible measure that satisfies Eq. (7) is a divergence defined as:

$$D(x\|y) = 1 - \max_{\alpha,\tau}\{\rho(x,y;\alpha,\tau)\};$$

$$\rho(x,y;\alpha,\tau) = \lim_{T\to\infty} \rho_T(x,y;\alpha,\tau) \tag{9}$$

where ρ is a Pearson correlation coefficient, defined using Eq. (8) by:

$$\rho_T(x,y;\alpha,\tau) = \frac{E_T[(x(t)-E_T[x(t)])(y(\alpha t+\tau)-E_T[y(\alpha t+\tau)])]}{\sqrt{V_T[x(t)]}\sqrt{V_T[y(\alpha t+\tau)]}} \tag{10}$$

This correlation coefficient can be easily simplified yielding:

$$\rho_T(x,y;\alpha,\tau) = \frac{E_T[x(t)\,y(\alpha t+\tau)] - E_T[x(t)]E_T[y(\alpha t+\tau)]}{\sqrt{V_T[x(t)]}\sqrt{V_T[y(\alpha t+\tau)]}} \tag{11}$$

It can be demonstrated (not included here due to the lack of space) that the measure of divergence in Eq. (9) is invariant w.r.t. μ, τ, α and λ, for $T \to \infty$, for signals having finite energy $E[x^2(t)]$. However, while this divergence answers to the need for a multiple invariant similarity measure, it is not always a reliable discriminating factor in the sense that there exists a wide range of signal pairs with the same correlation coefficient (the demonstration is also available). In order to better emphasize the divergence between the fault-free and the faulty situation, it is proposed to combine the previous divergence with an amplification factor that is compliant with the same invariants. Note that if the same idea of a correction factor is used for the similarity measures CID and d_s. A possible choice is:

$$\begin{cases} D(x\|y) = \left(1 - \max_{\alpha,\tau}\{\rho(x,y;\alpha,\tau)\}\right) a(x(t), y(\hat{\alpha}t + \hat{\tau})); \\ (\hat{\alpha},\hat{\tau}) = \arg\max_{\alpha,\tau}\{\rho(x,y;\alpha,\tau)\} \end{cases} \tag{12}$$

where:

$$\begin{aligned} a(x(t),y(t)) &= \frac{\max(e(x),e(y))}{\min(e(x),e(y))} \geq 1 \\ e(x(t)) &= \frac{\left\|\frac{d}{dt}(x(t) - E[x(t)])\right\|}{\sqrt{V(x(t))}} = \frac{\left\|\frac{dx(t)}{dt}\right\|}{\sqrt{V(x(t))}} \end{aligned} \tag{13}$$

The correction factor $a(x(t),y(t))$ corresponds to the term c_f used in the CID but computed between $x(t)$ and a delayed version of $y(t)$ that maximize the maximum correlation coefficient. The term $e(x)$, corresponding to CE in the CID, is normalized by the standard deviation. Note that it requires computing a derivative which is not trivial in a digital computer. Usual industrial solutions include the finite difference method or more advanced solutions such as the differentiators [5]. To take advantage of a logarithmic scale, an alternative definition of Eq. (12) is:

$$D(x\|y) = \ln\left(2 - \max_{\alpha,\tau}\{\rho(x,y;\alpha,\tau)\}\right) + \ln(a(x(t), y(\hat{\alpha}t + \hat{\tau}))); \tag{14}$$

The proposed candidate (14) of invariant divergence is now applied to a concrete example to show that there is still room for some improvement. Figure 6 depicts a flight scenario obtained thanks to an Airbus high-fidelity non-linear close-loop simulator where a liquid OFC has been injected at t=30s. This represents the elevator command and position (the exact numerical values are hidden for confidentiality reasons). Figure 7 displays the corresponding maximal correlation coefficient ρ, amplification factor a and the divergence in both linear and logarithmic forms. As can be seen between t=1 and 15s, in a fault-free situation during a dynamic manoeuver, there is a good correlation ($\rho \approx 1$) and the divergences are almost equal to 0. However, during a static phase (between 15 and 30s) command and position behave as two uncorrelated noises leading to a decrease of the correlation coefficient. Once the fault occurs the command reacts and oscillates at the same frequency. This is interpreted as a good correlation ($\rho \approx 1$ for t>30s) between command and position and prevents to correctly detect OFC thanks to a threshold-based logic on the divergence measures. It can nevertheless be noticed that the logarithmic divergence is numerically more advisable than the linear form. The divergence measure does not represent an efficient tool for OFC detection. A more robust measure is the coupling of "complementary" properties of ED and ρ: ED is sensitive to OFC but also to offset and measurement errors, while ρ is not necessary sensitive to OFC (depending of its frequency) but is not affected by offset and errors. So, the final similarity measure is given by (using a simplified notation):

$$D(x\|y) = (\ln(2-\rho) + \ln(a))d(x,y) \tag{15}$$

On the same example, it is clear (Figure 8) that the peaks in the ED between 1 and 15s are attenuated by the correlation coefficient. The loss of correlation due to a weak and noisy command (between 15 and 30s) is attenuated by the ED and for t>30s the OFC is emphasized by both the ED and the amplification factor a.

5. VERIFICATION AND VALIDATION

V&V facilities include flight test data, a desktop simulator and an aircraft model under Matlab environment (high-fidelity non-linear close-loop model of a generic Airbus aircraft). All V&V means are used for robustness analysis. OFC is a very rare event meaning that a very good robustness is required in order to not degrade the FCC Mean Time Between Failure (a.k.a. MTBF). For performance analysis real flight test data are not used as there is no control law reaction when injecting OFC. However, advantages of using flight test data include real actual sensor noise. V&V tools represent several dozen of flight hours in different aircraft configurations and flight points. The V&V strategy consists first in fixing the detection threshold that guarantees a robustness compliant with MTBF requirements. In a second step the performance study allows the minimum detectable amplitude to be determined. The performance analysis can be used for threshold tuning if the detection performance is not compliant with structural load requirements. There is a classical trade-off to ensure robustness and performance.

As the unknown OFC frequency influences the aircraft reaction, two dedicated strategies must be defined in parallel. The proposed solution is to apply a pre-filtering to use one dedicated strategy in each subband (low and high frequency). The filtering process allows noise to be reduced, offsets to be deleted and the initial detection problem to be split into two sub-problems for which threshold and sliding window length tuning is easier. For the high frequencies, as there is no law reaction, a simple distance such as CID or $d_s(x,y)$ can be computed on a sliding window. Once the distance exceeds a given threshold during a given time then an OFC is detected. For the low frequencies, the mixed similarity index (ED and logarithmic invariant divergence) is computed over a sliding window and is coupled to a threshold-based logic. The sliding window lengths are adapted to the lowest frequency of each subband and to the detection time constraints. Figure 9 illustrates the low-frequency strategy on a simulated example. In the left figure, the right upper part is a zoom around t=30s which clearly shows the flight control law reaction to the fault. On the right-hand side, the mixed similarity measure is displayed for two different sliding window lengths. Figure 10 shows the high-frequency strategy for the same example. The command U1 does not react to OFC and the fault is clearly exhibited thanks to the ED weighted by a correction factor. Both low and high-frequency strategies must operate simultaneously.

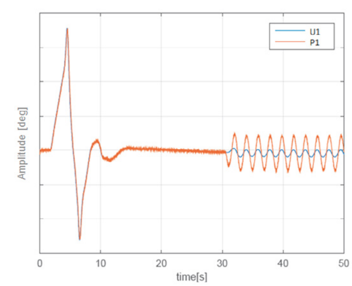

Figure 6: a flight scenario (elevator) with a liquid OFC.

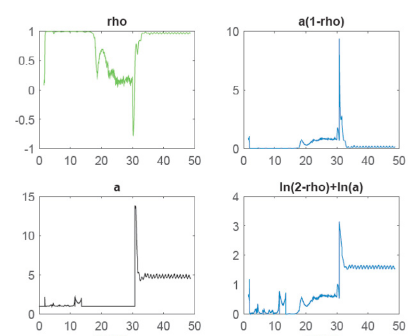

Figure 7: Maximal correlation coefficient ρ, amplification factor a and divergences corresponding to Figure 6.

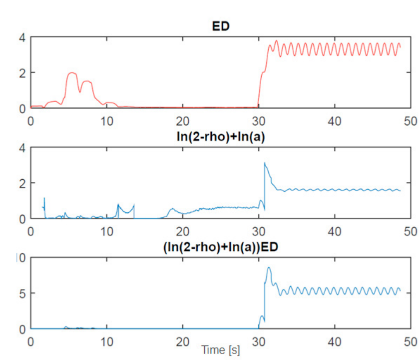

Figure 8: Mixed similarity measure between Euclidean Distance and logarithmic invariant divergence.

For confidentiality reasons it is not possible to show all the results of the on-going V&V campaign. The first results are encouraging and show that the proposed strategy could allow the current state of practice to be improved. Figure 11 compares the minimum detectable amplitudes obtained with both strategies, as a function of the OFC frequency (y-axis has been normalized). Even if the distance-based strategy is efficient, there is a performance degradation for the lowest frequencies. That is due to the flight control law reaction in the aircraft control mode frequency band, which generates a command signal very similar to the OFC signal.

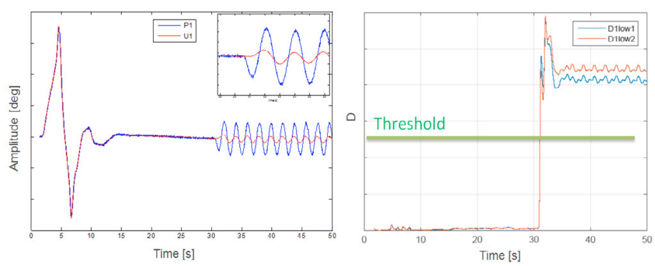

Figure 9: Low frequency strategy. Left: command and position. Right: mixed ED and divergence index.

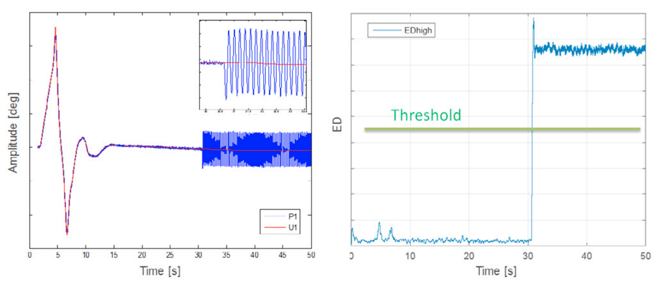

Figure 10: High frequency strategy. Left: command and position. Right: mixed ED and correcting factor index.

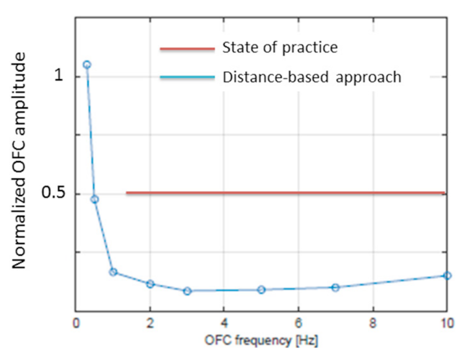

Figure 11: Minimum detectable OFC amplitude.

6. CONCLUSION

This paper presented a signal-processing strategy for the detection of failures impacting the Flight Control System. The proposed data-driven technique takes advantages of the loss of similarity between command and position when a fault occurs. Similarity measures based on an Euclidean distance weighted by correction factors were investigated and showed promising results. In particular, a new divergence measure was proposed. Based on preliminary tests, this new measure showed that the current model-based techniques can be significantly improved. The advantages of the proposed data-driven approach include genericity (the solution can be adapted to a different context) and low computational load (not detailed in this paper). Defining a clear methodology for threshold tuning represents an appealing avenue for future works. Moreover, the properties of the proposed divergence index should be theoretically studied in more details. Finally, a more comprehensive V&V campaign is necessary to confirm the preliminary results.

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