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Air Data Virtual Sensor: a Data-Driven Approach to Identify Flight Test Data Suitable for the Learning Process

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Abstract Governments and main stakeholders from all over the world will make available huge funds to develop a greener aviation. To this aim, important updates are expected in the next years in aerodynamics, A/C configuration, propulsion and onboard systems. In addition, the next advent of the UAVs civil operability, and possible complexity deriving from high level of redundancy, is pushing the aerospace community towards the use of new technologies for a smarter A/C system integration. As far as avionics is concerned, the trend shows that the new avionic paradigms, e.g. Fly by Wire and distributed avionics that are successfully applied on large passenger aircraft (e.g. Airbus A380), will be commonly used even on smaller aircraft. The digital revolution experienced in last decades will be crucial to achieve a smarter integration of onboard systems. Air Data Systems will be updated, the most are still based on pneumatic probes or vanes, in order to enable beneficial avionic integration. In recent years, several studies were conducted for a smarter sensor fusion to be used to provide alternate sources of air data with the aim to detect ADS faults avoiding common modes and to provide analytical redundancy. The present work is part of the Smart-ADAHRS project that is born aiming to design a simplex complete air data system partially based on virtual sensors. The main objective of the aforementioned project is to provide an innovative ADS with a lighter configuration (some sensors are replaced by virtual ones) assuring the same performance and reliability of commons ADS. At the moment, the authors are involved to correlate flight test, obtained with a flying demonstrator on an ULM aircraft, and simulated environment performance. The virtual sensors are based on neural network techniques and, therefore, the learning process is crucial to obtain suitable performance. Moreover, using real flight data introduced new uncertainties to the

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training data set that required a pre-processing of the training data. The present work describes the approach used to extract quasi-steady and quasi-symmetric data from the entire flight data record. The main objective of the tool is to avoid common issues in MLP training (e.g. local minima) and to promote a more uniform distribution of the training data set inside the n-dimension domain where the neural networks are defined.

1 Introduction

The *more electrical aircraft* is one of the most challenging objectives of the aviation industry and its suppliers. A lot of researches are conducted in order to bring significant innovation onboard aircraft with the main aim to increase performance and safety, to reduce fuel consumption and emissions [12, 6]. Both industrial players and governments from all over the world are very sensitive to the latter topics, and many funds and effort have been, and will be, available in next years to achieve well defined goals. For example, in Europe, the European Parliament has allocated a huge budget to help the transition towards a greener and safer aviation [13]. A helpful resource to get those goals, is the advent of digital revolution. The more relevant role of avionics in flight control and management have pushed aircraft technology towards new limits. Fly by wire, distributed architectures, are only two of the main results achieved by the aerospace community that are certified to fly in our skies. Novel architectures, such as the FBW, are successfully applied to large (Airbus A380) or military aircraft (Leonardo M-346) and will be the new standard for civil aviation and small aircraft transport (SAT) communities in next years [24, 11]. An example is the H2020 - Clean Sky 2 (under SYS ITD area with Grant Agreement number 821140) project *MIDAS*.

The novel avionic standards involve the entire A/C architecture and each line replaceable unit (LRU) because, in order to fully exploit benefits from digital avionics, a smarter integration of all A/C subsystems is needed. Within this scenario, Air Data Systems (ADS) need to be updated for an advantageous integration into modern digital avionic systems. In fact, ADS applications are still based on different probes and vanes (used as direct sources of air data: static pressure, angle of attack, etc.) that are installed externally on the A/C fuselage, connected to a central Air Data Unit (ADU) to provide the necessary information to the pilots (or a flight control computer).

From this point of view, it is clear that ADS is one of those avionic systems to be involved in the digital avionic updates and the integration of classical ADS LRUs (e.g. probes and vanes) within the modern FBW architecture is not the smartest way. In fact, in order to overcome the drawback to connect probes and vanes to ADUs pneumatically and then ADU to the Flight Control Computer (FCC), many recent large FBW A/C are equipped with *integrated* probes which are based on a probe (or a vane) combined with its own transducer/s. In this latter case, the single air data LRU can be digitally connected to the FCC. As well known, ADS system should be replicated independently in order to achieve the reliability requirements of applicable category standards (e.g. CS23, CS25): triplex ADS is a standard for civil aviation. At the moment of the present work, there is not yet a well-defined standard for unmanned aircraft. Most likely, UAVs will satisfy very strict requirements in terms of safety and reliability that could even bring to a quadruplex ADS architecture.

Within this perimeter, analytical redundancy, or virtual sensor, has become a more familiar concept in recent years, because the avionic background is today mature to welcome such innovations [9, 20]. This approach enables the replacement of physical ADS probes and/or vanes (used for redundant purposes) with virtual ones with consequent benefits in terms of weight, power consumption, reliability, maintainability and emissions. The advent of distributed networks (A380, A400M, A350, B787, etc.) has been seen as a significant booster for a better exploitation of onboard data to be used, for instance, as part of a redundant Flight Control System architecture. In fact, following the analytical redundancy approach, some innovative techniques are used to virtually synthesise air data sensors [2, 22]. A redundant ADS with some LRUs based on virtual sensors can lead to several benefits when guaranteeing the same performance. Firstly, the whole ADS safety level is improved. The redundant ADS based on virtual sensors provide some quantities not fully related to the air environment that is affected by external agents (e.g. ice, dust, sand, etc.). This is crucial to overcome some issues related to common failure modes or incorrect failure diagnosis of modern ADS [10, 19]. The second aspect is related to simplification of the whole ADS architecture. Redundancy aspect is quite easy to be treated on large passenger aircraft where there are no particular limitations for air data sensor installation on the fuselage and cable/tube displacement inside the fuselage. Whereas, the same operation can become very challenging when the fuselage dimensions reduce (business aircraft, SAT or unmanned). Other benefits are related to improved fuselage aerodynamics, lower power consumption (mainly for de-icing purposes) and emissions of ADS architectures based on virtual sensors.

In this scenario, the current research puts its roots. In fact, the aim of the current project, named Smart-ADAHRS (Smart-Air Data, Attitude and Heading Reference System), is to provide the same flight parameters with a lighter impact on the ADS architecture [18, 4] but at the same time guaranteeing the same level of performance of common ADS [8]. The present work describes a helpful tool suitable for a smarter design of virtual sensors based on Machine Learning.

2 Background

From a general point of view, a common simplex ADS provides some data to pilots or automatic control system needed for the correct piloting, control and navigation purposes. The complete air data set is made up of the following direct measurements:

- Dynamic pressure for airspeed indication

- Static pressure for barometric altitude and vertical aircraft separation
- Air temperature for true air speed calculation
- Angle of attack for stall indication
- Angle of sideslip for navigation purposes

The Smart-ADAHRS aims to provide an innovative air data system partially based on virtual sensors. In particular, the proposed ADS solution is based on direct measure of dynamic pressure, static pressure and temperature while the aerodynamic angles are estimated as an indirect measure by means of data fusion between measured air data available and inertial data as described in [15]. Virtual sensors are based on neural network techniques, as presented in previous works [5, 16]. The core of the Smart-ADAHRS project relies in exploitation of available data from independent sources to provide an estimation of the aerodynamic angles, angle of attack (α) and angle of sideslip (β).

According to the Universal Approximation Theorem, a Multilayer Perceptron (MLP) is able to uniformly approximate any function inside the $[0;1]^n$ hypercube. The key-to-success to design an accurate MLP, obviously, is the training data set used for the learning process. The training stage, based on flight data, therefore, is crucial for the correct learning process of the virtual sensors.

For this work, flight data collection is the result of a collaboration between different entities. The Smart-ADAHRS technological demonstrator was developed by Politecnico di Torino and AeroSmart S.r.l. and it is able to record all the input signals needed by the MLP. Target values (AOA and AOS) are measured by the Flight Test Instrumentation (FTI) developed by the Politecnico di Milano [14], which manages the flight test campaign of the ULM. The test aircraft is the G-70 from Ing. Nando Groppo S.r.l. [1].

In previous works, it emerged that the training data set needs some pre-processing manipulations in order to avoid common learning issues [17]. The local minima effects is mitigated with several techniques, e.g. splitting flight data, re-training with different initial values, a quasi-uniform hypercube distribution is beneficial. The latter is obtained by means of dedicated flight test campaign, with dedicated manoeuvres able to cover most of the flight envelope and exciting the aircrafts natural modes. Moreover, the quasi-uniform distribution of flight data inside the hypercube is beneficial to avoid that the MLP minimise the mean error mainly in local area rather than on the entire hypercube. It was noted that the ULMs flight data collected are more numerous during dynamic rather than steady flight conditions.

The present research aims to present an academic tool able to automatically extract those manoeuvres from the entire flight records that are needed for the best MLP training. The main aim of this approach is to limit the flight test requirements for VS training and to populate the learning data set with the following quasi-steady flight conditions:

- Horizontal uniform flight
- Glide path at constant vertical speed
- Turn at different rates

The objective of the present work is to present the score assignment tool performance able to enrich the training data set with quasi-static data when the majority of flight data is related to dynamic conditions.

3 Methodology

This section describes the method applied to find the stationary and quasi-stationary points in a generic flight data collection. A key aspect of this analysis is the definition of quasi-stationary and quasi-symmetric flight condition.

Loosely speaking, ideal longitudinal equilibrium conditions are rarely obtained in flight test, due to residual variation of the flight parameters and the noise acting on them. The analysis is based on dedicated test points and the assumption of validity of the measurement grounds on experience, FTI performance, atmospheric and meteorological reasons. Relaxing the contraints on the flight parameters, that is with the assumption that a slight deviation from the ideal value can be accepted, it is possible to define the *quasi*-stationary and *quasi*-symmetric flight conditions. In case of this particular Machine Learning data analysis, it is not specifically required a perfect longitudinal equilibrium. Hence, this method provides a set of data corresponding to flight conditions close to the ideal longitudinal equilibrium, without any analysis of the dataset and without planning dedicated manoeuvers.

The main procedure is based on the assignation of a value called *score* to a given instant. The maximum score is given to symmetric and stationary equilibrium flight condition so that it is possible to select the desired instant observing this value. Actually, the score is not assigned directly to the n-dimensional vector associated to the flight condition but a score is firstly assigned independently to the various flight parameters and eventually the final score is obtained from the signal scores (e.g. the average). See Algorithm 1 for details.

At the beginning, the signals are divided in non-overlapping time windows. The length of the time windows is constant and it has been taken as 5 s. The length of the time-window is obtained as a trade-off between finding an actual stationary point and the efficiency of the algorithm. In fact, longer time window will bring to a more reliable evaluation of the flight condition whereas shorter time window will bring to extra points in the final result. Afterwards, some statistics of the signal during each time window are evaluated. Because of this statistical analysis, the original sampling frequency of the signal can have an important influence on the final result. In fact, the number of elements in each subdivision must be sufficiently high such that the sample estimators are statistically valid. In this work, original sampling period is about 0.05 second, corresponding to 100 elements per interval, which is sufficiently high. The original sampling period comes from the sampling frequency of the FTI.

Algorithm 1: Quasi-Stationary and Quasi-Symmetric flight conditions detection algorithm

```
Data: Flight data
Result: Set of quasi-symmetric and quasi-stationary flight conditions
Partitioning in 5 s-long time windows;
foreach time-window do
    foreach signal do
        Evaluation of the statistics of the signal during the time-window;
        Assign a score to each signal;
    end
    FinalScore = average(signal scores at the current time-window);
    if FinalScore > threshold then
        Store as valid time-window
    end
end
```

For each interval sample mean, sample standard deviation and the deviation between the minimum and maximum values covered by the signal inside the sample are calculated. A score is hence assigned to each interval depending on the descriptive values calculated beforehand. The decision on which statistics consider for the score assignment grounds on the type of signal evaluated. In some cases, the score depends on how much the sample mean is close to a given value. For instance, the angular rates must be zero in stationary conditions. In other cases, when the interest falls in observing a constant signal, the sample standard deviation or the maximum deviation drives the score assignment. For instance, the closer the maximum deviation of the impact pressure is to zero, the higher is the assigned score.

The rules governing the score assignment to a given sample has not a unique solution. In this paper, a piecewise linear function is implemented but, according to the authors, several other possibilities exist. To enhance the score assignment, the standard deviation of the sample is always accounted in this work. This helps to increase the score of the stable sample with respect to sample affected by high variability. See Sect. 3.1 for the complete description of the score assignment process.

When every signal has been sampled and the signal score has been assigned, the final sample score is evaluated as the mean of the scores among the signals. A weighted mean could be implemented here. However, it implies the definition of which signal is considered the most important during this evaluation and without this consideration a weighted mean cannot be implemented.

Once the scores have been obtained, the selection of the stationary and quasi-stationary points can be carried out. This procedure involves the definition of a minimum score threshold necessary to pick or not a sample, given the scores assigned to each sample. The previous steps are applied equally to each flight test. For this reason, the scores are comparable among different flights. However, it has been observed that a normalization procedure greatly simplifies the decision process. In fact, subtle differences exist between quasi-stationary and quasi-symmetric conditions. To better explain this, it must be recalled that this method can obtain a set of points on the flight envelope slightly relaxing the trim condition constraints. In some cases, very low time derivatives and deviations can be observed. However, the attitude could be too much asymmetric to be neglected. At the same time, a slightly more symmetric flight condition but corresponding to higher deviation on the measures than the previous case can be considered valid. The problem of defining when a flight condition is quasi-symmetric and quasi-stationary is obviously ill-posed. This paper shows that it can be converted on the problem of defining a threshold on the score, that unfortunately fails to be a metric. Moreover, if the score is normalized, the equivalence between asymmetry and stationarity in the score space seems to be well faced. At the time of writing this paper, this effect does not have any mathematical justification. However, as said before, a good accordance with flight test measurement has been observed with this procedure.

3.1 The score assignment process

This subsection shows more details on how a sample of a signal has been related to a scalar value. This step is crucial for the effective functioning of the algorithm. Two different solutions have been applied.

Mathematically speaking, given a signal $x_i = x_i(t)$ it is possible to extract a sample $x_i[n] = E[x_i(t)]$ with $(n-1)t_s \le t < nt_s$. Various statistics θ of the sample $x_i[n]$ can be measured. Eventually, the score s is assigned to the n-th sample based on the corresponding $\theta(n)$ as in the following relation:

$$s = s(\theta(n)) = s(n) \tag{1}$$

The first approach on the functional form for s is obviously linear. The *triangle function* can be generally defined as in Eq. 2. An example can be seen in Fig. 1.

$$\Lambda(x) = \begin{cases} 1 - \frac{|x|}{x_{th}} & \text{for } |x| < x_{th} \\ 0 & \text{for } |x| \ge x_{th} \end{cases} \tag{2}$$

Setting $s = \Lambda(\theta(x[n]))$ a first evaluation of the sample score can be obtained. For instance, if the q_c signal is considered, the maximum acceptable Δq_c during 5 s

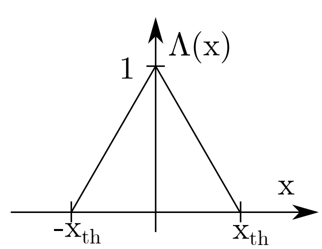

Fig. 1 Example of triangle function $\Lambda = \Lambda(x)$

can be set to 100 Pa. In this case, if the maximum deviation is higher than Δq_c then a null score will be assigned. At the same time, if the maximum deviation is between 0 Pa and 100 Pa, then a proportional score will be assigned to that given sample.

However, it has been found that extending the previous analysis to more than one single statistic brings to higher coefficient of determination with respect to using only one statistic.

Eq. 2 can be modified considering similarities to a triangulation problem. In fact, it is possible to take advantage of the first order Lagrange basis to model the score function.

Given $x_1, x_2, y_1, y_2 \in \Re$ with $x_1 < x_2$ and $y_1 < y_2$ it is possible to identify four regions as reported in Fig. 3.

Let $P \in \Re^2$ a point belonging to the Oxy space, it is possible to write

$$P \in \mathscr{R}_1 \Leftrightarrow \begin{cases} y_P > y_{s_1} \\ x < x_m \\ y < y_m \end{cases}, \quad P \in \mathscr{R}_2 \Leftrightarrow \begin{cases} x \geq x_m \\ y < y_m \\ y_p > y_{s_2} \end{cases}, \tag{3}$$

$$P \in \mathscr{R}_3 \Leftrightarrow \begin{cases} x \geq x_m \\ y \geq y_m \\ y_P < y_{s_3} \end{cases}, \quad P \in \mathscr{R}_4 \Leftrightarrow \begin{cases} x < x_m \\ y \geq y_m \\ y_P < y_{s_4} \end{cases} \tag{4}$$

Defining $s_i(x) = l_i(x)$ s.t.

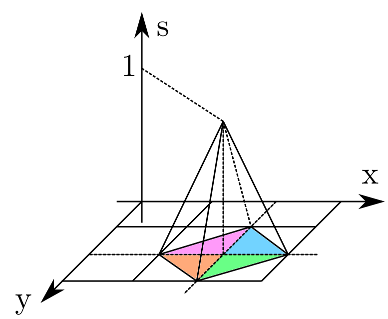

Fig. 2 Generalization of the score function using the First Order Lagrange basis

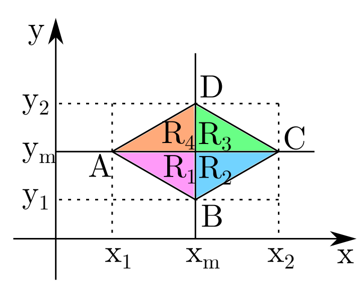

Fig. 3 Definition of the regions in a generic Oxy plane

$$l_i\left(x_j\right)=\delta_{ji}=\begin{cases}1 & \text{for } i=j\\ 0 & \text{for } i\neq j\end{cases} \tag{5}$$

and

$$l_i\left(x\right)=\frac{\prod_{j\neq i}\left(x-x_j\right)}{\prod_{j\neq i}\left(x_i-x_j\right)} \tag{6}$$

Once the region in which P belongs to has been found, it is possible to write Eq. 7 as follows:

$$\nabla s_i\cdot\left(\overline{x}-\overline{x_i}\right)=s_i\left(\overline{x}\right)-s_i\left(\overline{x}_i\right) \tag{7}$$

where $\overline{x}$ represents the vector of coordinates of the point P. Moreover,

$$\nabla s_i\cdot\left(\overline{x}_m-\overline{x}_i\right)=s_i\left(\overline{x}_m\right)-s_i\left(\overline{x}_i\right)=1 \tag{8}$$

$$\nabla s_i\cdot\left(\overline{x}_{i+1}-\overline{x}_i\right)=s_i\left(\overline{x}_{i+1}\right)-s_i\left(\overline{x}_i\right)=0 \tag{9}$$

The following linear system can be written:

$$\begin{bmatrix}x_m-x_i & y_m-y_i\\ x_{i+1}-x_i & y_{i+1}-y_i\end{bmatrix}\begin{Bmatrix}s_{i,x}\\ s_{i,y}\end{Bmatrix}=\begin{Bmatrix}1\\ 0\end{Bmatrix} \tag{10}$$

which brings to Eq. 7,

$$s_{i,x}=\frac{y_{i+1}-y_i}{\det\mathbf{G}} \tag{11}$$

$$s_{i,y}=-\frac{x_{i+1}-x_i}{\det\mathbf{G}} \tag{12}$$

representing the two partial derivatives of the score function s with respect to x and y, where $\mathbf{G}$ is the matrix at the LHS of Eq. 10.

Eventually, the score assigned to any sample $x_{i,n}$ is evaluated as follows:

$$s\left(x_i\left[n\right]\right)=\nabla s_r\left(\overline{x}-\overline{x}_i\right)+s_i\left(\overline{x}_i\right) \tag{13}$$

With this formulation, two statistics can be considered. In this paper, the standard deviation of the sample is always applied as second statistic. This help to increase the score for stable samples.

Table 1 shows the values used in this paper.

4 Results

This section shows the results obtained by the proposed score-assignment method on a flight test campaign conducted in the north Italy during June 2017. A total amount of 18 flight tests have been collected on a Ultra-Light Machine (ULM) named G70

Table 1 List of signals and corresponding statistics

Signal	First statistic	Value	Second statistic (Standard deviation) value
Angular rate	Sample mean	$0.01\,\mathrm{rad\,s^{-1}}$	$0.005\,\mathrm{rad\,s^{-1}}$
Altitude	Max deviation	1 m	0.5 m
Vertical speed	Sample mean	$1\,\mathrm{m\,s^{-1}}$	$0.5\,\mathrm{m\,s^{-1}}$
Acceleration	Sample mean	0.05 g	0.025 g
Impact pressure	Max deviation	100 Pa	50 Pa
Pitch angle	Max deviation	2°	1°
Roll angle	Sample mean	1°	0.5°
Yaw angle	Max deviation	1°	0.5°

and manufactured by Ing. Nando Groppo. The G70 is a propeller driven aircraft with traditional wing-tail configuration, 2 seats, non-retractable landing gear. A fully-fledged FTI suite developed by Politecnico di Milano is installed on-board. This FTI system, called Mnemosine, is capable of supporting certification procedures [14]. Its design has been tailored for ULM and it consists of a low cost, low intrusive and flexible solution for flight testing. A second equipment, the Smart-ADAHRS demonstrator, is installed together with Mnemosine. This system is equipped with an independent ADAHRS platform integrated with GNSS. The only parts shared by the two systems are the pressure ports, probes and the first segment of pneumatic links. The aerodynamic angles of the aircraft have been measured by two vanes mounted on a Pitot-boom structure.

The flight tests have been collected during a Master course held in Politecnico di Milano. Students themselves cover the Flight Test Engineer (FTE) position, bringing in some cases to incomplete observations. In some cases, fuel data consumption are missing, in some others the flight control surface position have not been recorded. However, the method showed good capabilities to face this medium degree of uncertainty. An example of the flight data recorded during one flight test can be seen in Fig. 4.

To evaluate the capability of the method, the $C_L - \alpha$ plot is obtained. Because no engine measurement is available on-board, a fuel consumption linearly descreasing with time has been assumed. In this way, it is possible to evaluate the lift coefficient as $C_L = \frac{mg}{q_c S}$, where m is the aircraft mass, g is the gravitational acceleration, q_c is the impact pressure and S is the wing surface area. The samples resulted to be organized on a straight line, with slope $C_{L\alpha}$ and zero α_0 close to the independent analysis previously conducted by [3]. To avoid nonlinear effects, only the samples with $\alpha < 10°$ have been taken in consideration. A maximum error of $-0.06\,\%$ on $C_{L\alpha}$ and of $-2.27\,\%$ on α_0 has been obtained. The quality of the linear regression has been measured with the coefficient of determination.

Actually, the effects of $C_{L\delta_e}$ and asymmetric flight condition should be accounted in a post-processing correction. Shortly, according to [7], the slope obtained by the regression should be properly called $C^*_{L\alpha}$. However, the difference between $C^*_{L\alpha}$ and $C_{L\alpha}$ has been here dropped for sake of clarity.

It is interesting to note that the obtained samples organize on three straight lines. In fact, some of them corresponds to flaps down in Take-Off (about 14°) and Landing (about 36°) conditions. Because the flap angle deflection, for leading edge plain flap, is equivalent to offset the null lift direction with an angle proportional to the δ_f, it is possible to identify two analytic values of $\Delta\alpha$ to compare our results. In fact

$$\Delta\alpha = \tau\delta_f \tag{14}$$

In this work, to assess the accuracy of the method, the effect given by the flap on α_0 has been evaluated. Considering a 2-dimensional $\tau_{2D} = 0.5$ [23] and a surface ratio $S_f/S = 0.66$, the 3-dimensional value for $\frac{\partial\alpha}{\partial\delta_f}$ becomes $\tau_{3D} = 0.33$. Unfortunately, this value is valid up to 20° of flap deflection. The κ' parameter [21] has been used to extend the evaluation beyond this limit, leading to the following more general formulation:

$$\tau_{3D} = \tau_{2D} * \kappa' * \frac{S_f}{S} \tag{15}$$

Therefore, the following values are used in this paper $\tau_{3D,14^\circ} = 0.33$, $\tau_{3D,36^\circ} = 0.27$.

Looking at the Fig. 5 it is possible to identify all the sample points obtained with $s(i) \geq 0.667$ and $\delta_f = 0^\circ$.

Fig. 6 shows the samples corresponding to flaps in TO condition, whereas Fig. 7 collects the sample obtained in LND condition.

It is important to notice that no flight control surface data has been directly applied into the score assignment. In fact, the flap deflection angle δ_f has been used only in post-processing to distinguish Fig. 5–Fig. 7, in order to clearly identify the three linear regression.

The comparison of the regression with the independent analysis conducted by Battaini [3] confirms the validity of the method. Table 2 collects the results obtained. A difference about -0.06% has been obtained on $C_{L\alpha}$ with respect to the

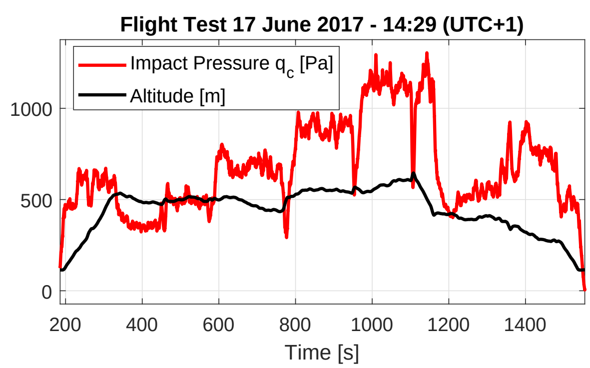

Fig. 4 Example of flight test data reporting the impact pressure q_c and the altitude

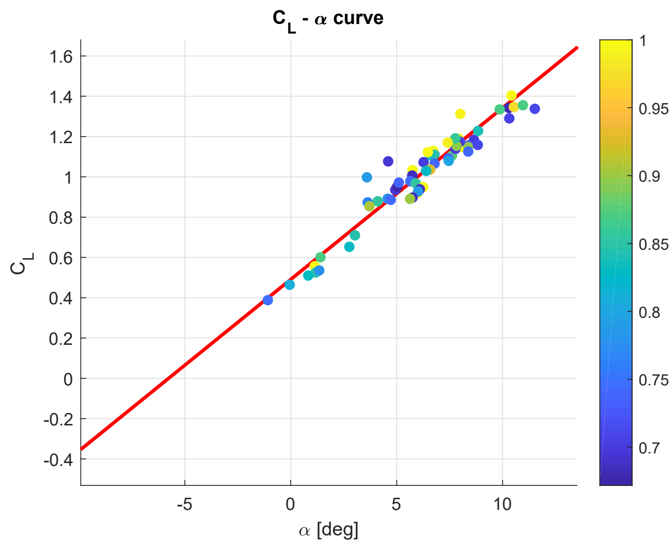

Fig. 5 $C_L - \alpha$ plot, clean condition, $\alpha_0 = -5.7673°$, $C_{L,\alpha} = 0.085136 deg^{-1} = 4.8779\,\mathrm{rad}^{-1}$, $R^2 = 0.95812$. Scatter plot color corresponds to the sample score.

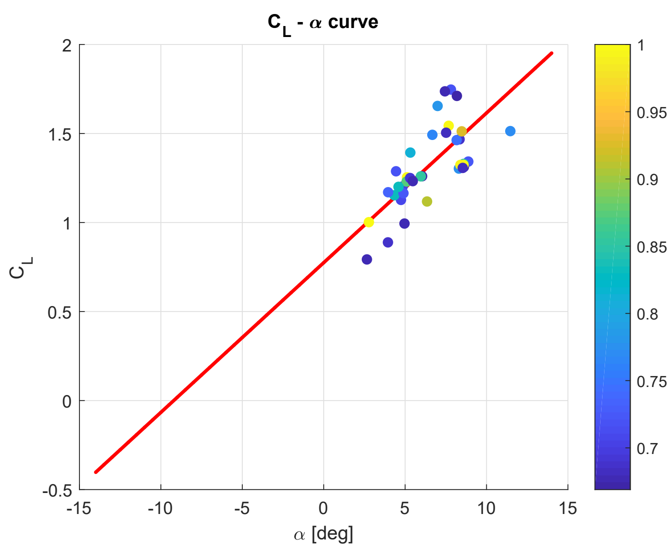

Fig. 6 $C_L - \alpha$ plot, TO condition, $\alpha_0 = -9.2128°$, $C_{L,\alpha} = 0.084072 deg^{-1} = 4.817\,\mathrm{rad}^{-1}$, $R^2 = 0.70726$. Scatter plot color corresponds to the sample score.

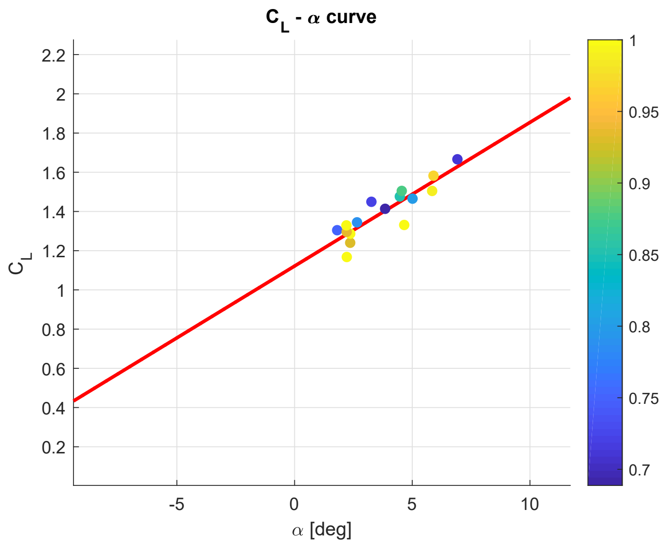

Fig. 7 $C_L - \alpha$ plot, LND condition, $\alpha_0 = -15.3087°$, $C_{L,\alpha} = 0.073267 deg^{-1} = 4.1979\,\mathrm{rad}^{-1}$, $R^2 = 0.88861$. Scatter plot color corresponds to the sample score.

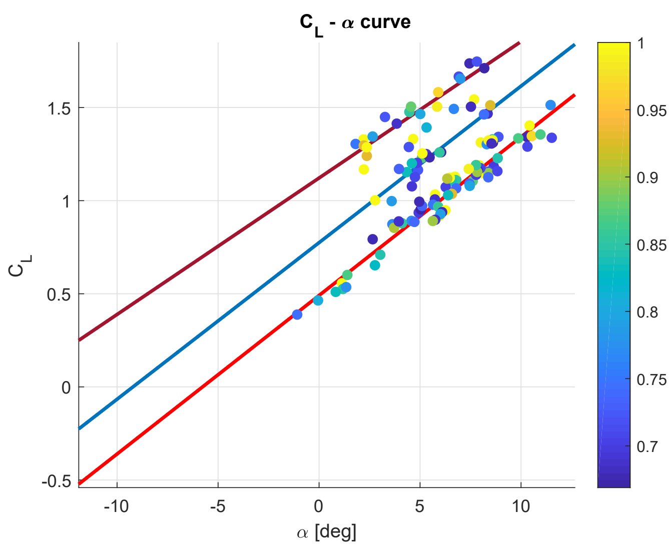

Fig. 8 $C_L - \alpha$ plot, global view of the three regression lines

manual derivation, neglecting the effect of the elevator. For what concern the α_0, the difference is about $-2.27\,\%$.

Source	$C_{L,\alpha}$	α_0	R^2
Battaini [3]	4.881	$-5.9015\,$deg	-
Regression, clean	4.8779	$-5.7673\,$deg	0.95812
Regression, TO	4.817	$-9.2128\,$deg	0.70726
Regression, LND	4.1979	$-15.3087\,$deg	0.88861

Table 2 Result on the estimation of $C_{L,\alpha}$ and α_0

To evaluate the accuracy of the regression in TO and LND conditions, a manual estimation has been carried out. Hence, although the coefficient of determination of the linear regression is lower than 0.9 for the TO and LND conditions, the obtained results can be considered a good demonstration of the trim identification method, due to the accordance with the analytical estimation.

5 Conclusions

With the larger use of digital solution in avionics, analytical redundancy and virtual sensors are more familiar concepts. The FBW solutions, successfully applied on larger passenger aircraft, will be even used by Small Air Transport community following the path towards a greener aviation. The present work is part of the Smart-ADAHRS project that has as final goal to design a simplex and complete Air Data System architecture partially based on virtual sensors. The virtual sensors are dedicated to aerodynamic angle estimation exploiting neural network techniques. In order to achieve accurate and reliable virtual sensors, the training stage is a crucial part of the learning process. At the moment, the virtual sensors are implemented on a flying demonstrator to be used in real time during flight tests. The flight trials highlighted the need to flight manipulation before the learning process in order to achieve a more balanced distribution of the flight data among the n-space dimension of the VS definition.

A method for the automatic identification of the quasi-stationary and quasi-symmetric situation in a flight test database has been described in this paper. The method is based on a down sampling technique followed by a linear multivariable score assignation. If the mean value of the signal scores at a given time is greater than a given threshold, it can be stated that it is a quasi-stationary and quasi-symmetric point and it is valid, under some assumption, to be applied in several application. The validity of the method has been assessed with the estimation of $C_{L\alpha}$ and α_0. The comparison of the results with values estimated independently by means of classical Flight Test procedure confirms the validity of the method.

The proposed method worked also in flaps down conditions and the comparison on the corresponding $\Delta\alpha_0$ has been conducted with analytical analysis, showing good accuracy. Although these are preliminary results, the authors think that the method can be analysed thoroughly to improve its performance.

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