Synthetic Air Data System: An alternative to conventional sensors

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Abstract

A standard Air Data System is comprised of several conventional sensors that, together, provide key information regarding the air surrounding an aircraft. An example of this is the case of the aircraft’s airspeed, which is highly dependent on a pitot tube sensor. A sensor of this type can be obstructed due to icing, leading to wrong measurements of the airspeed, and a common solution consists of installing at least three sensor units, in order to obtain a physically redundant system. An increase in the number of sensors, brings about an increase in the complexity and weight of the system, which in the case of Unmanned Aerial Vehicles may not be desirable or even impossible to achieve. The present thesis studies the possibility of using two approximate kinematic models of an aircraft, applied in a Least Mean Squares algorithm, to estimate the wind field and aircraft’s airspeed. By exploiting the aircraft’s maneuvers, and relying on measurements from a GPS and an AHRS, a system was designed that acts as a “virtual” redundant system, to help in the estimation of airspeed. The conditions underlying the design of the proposed system were studied and validated, and the limitations of the algorithm for airspeed estimation, when the aircraft is subjected to unexpected situations, were analyzed. The work concludes by proposing improvements to the method derived, using more accurate models of the aircraft’s kinematic and exploiting alternatives to optimize the computational effort required.

Keywords: Air Data System, Pitot tube, Least Mean Squares, Airspeed estimation, Wind estimation.

1. Introduction

An Air Data System is a key item for the well functioning of all avionic systems during flight, and it consists of aerodynamic and thermodynamic sensors and associated electronics [1]. This system is in charge of collecting and processing air data and then present it to the pilot through flight displays or forwarding it to other sub-systems, such as autopilots, weapon system fire control computations, and control of cabin air pressurization systems [1]. Data such as pressure altitude, vertical speed, calibrated airspeed, true airspeed, mach number, angle of attack, static air temperature, and air density ratio are examples of the data processed by this system.

The concept of a Synthetic Air Data System came to light as a method of estimating standard parameters without the use of classic sensors. Zeis [2] is often acknowledged as one of the pioneers on this concept. His work is rooted in previous theoretical work [3, 4, 5, 6] on the estimation of the angle of attack $\alpha$, that borrows from the results in Duane Freman [4], where $\alpha$ is estimated using as measured data, acceleration inputs and surface positions during a given maneuver. Taking use of standard inertial measurement units, Zeis [2] assumed the availability of airspeed measurements along with accurate knowledge of the lift coefficient $C_L$ to estimate the angle of attack, and found the estimator to be highly feasible.


Later, Srikanth Gururajan et al. [10] explored the possibility of accommodating Artificial Neural Networks in a sensor failure detection scheme and evaluated two networks: the Extended Minimal Resource Allocating Network and a Multilayer Feedforward NN. Both were validated with flight data and had similar performance as online estimators in what concerns the standard deviation of the air-
speed tracking error.

Rudy et al. [11] studied a model-free method that excludes the use of pitot tubes. The approach relies on a nonlinear Kalman filter that estimates the airspeed fusing measurements from an IMU, GNSS, and wind vanes.

In 2014, C. Hurter et al. [12] attempted to extract wind parameters out of the analysis of the trajectory of several aircraft. Using a 2D approach and neglecting the vertical wind component, they presented a solution that, with enough measurements, could estimate the North and East components of the wind, making use of a Least Mean Squares algorithm.

Nowadays, the increase of the necessity of drones in a wide variety of situations is undeniable, and in most of these vehicles, there is not the possibility to install as many pitot tubes as in a regular aircraft, and the identification of a fault can be very difficult or even impossible to achieve. Along with this inconvenience, it is added the fact of the acquisition of the dynamic model of an aircraft to be a complex and time consuming operation. It is in this context that the present research was conducted. The main goals of this work was to investigate and build a Synthetic Air Data system, capable of estimating the airspeed of an aircraft, with the least amount of sensors at hand.

In short, the contributions of this work are the following:

- Given a yaw maneuver, for a steady flight, provide real-time estimation of the airspeed and the wind field, eliminating both the use of a dynamic model and a pitot tube sensor;
- After successfully estimating the wind field, provide a time limit to use past wind estimations in a situation in which, the continuous estimation of the wind is not possible;
- Provide a "virtual robustness" framework to back up the standard air data system.

2. Synthetic Air Data System

The work of C. Hurter et al. [12] had a big impact on the present thesis. In their work, the idea was to use radar measurements of position and velocity over time, and analyse the trajectory of several aircraft as a way to estimate the wind velocity. Analysing the ground speed and ground course of one or more aircraft relative to the ground, they realized that these two had a sinusoidal shape relation, which could be explained by the influence of the wind on the aircraft.

By exploiting the Least Mean Squares algorithm, and assuming the wind field and airspeed to remain constant within a certain time interval, they were able to successfully estimate the wind components, fusing data from several aircraft.

This idea of considering an approximate kinematic model, during a given maneuver, to provide the necessary information to estimate the wind field, and therefore, the airspeed, was found to be a good exploit as to the acquisition of the required parameters.

A key factor for the final version of the algorithm is for it to present a model accurate enough to describe the kinematic of the aircraft. In this work there were considered two separate ones, described in section 4.

3. Least Mean Squares

The method of Least Mean Squares (LMS) is a procedure to determine the parameters that best fit a certain model to a cluster of data, using simple calculus and algebra.

Assuming we have a set of observations $x(n) = x_1,...,x_N$ and we want to predict an output $y(n) = y_1,...,y_N$, it is safely assumed that the variable $y(n)$ can be approximated by a function that depends on the observations made: $\hat{y}(n) = f(x(n), \theta)$, where $\theta = [\theta_1,...,\theta_k]$ is a vector of $k$ parameters to be estimated. To state that $y(n)$ can be approximated to $\hat{y}(n)$ is to state that they differ from an error, or residual, $e(n)$, that is,

$$y(n) = \hat{y}(n) + e(n)$$  \hfill (1)

To evaluate the efficiency of the estimation, the Least Squares method defines an energy criterion, defined as the sum of the squared errors:

$$E(\theta) = \sum_{n=1}^{N} (y(n) - \hat{y}(n))^2$$  \hfill (2)

which can be written as:

$$E(\theta) = \sum_{n=1}^{N} (y(n) - f(x(n), \theta))^2$$  \hfill (3)

The values $\theta$ that best fit the model are the ones that minimize the Least Squares energy:

$$\hat{\theta} = \min_{\theta} E(\theta)$$  \hfill (4)

When the model has a linear nature: $f(x, \theta) = \gamma_1(x)\theta_1 + ... + \gamma_\mu(x)\theta_\mu$, the problem can be formulated and solved using matrix notation, as follows,

$$y(n) = H(n)\theta$$  \hfill (5)

where $y$ is the observation matrix, $H$ the matrix describing the system, and finally $\theta$ the parameters to be estimated.
If the matrix $H$ has full rank, i.e., if there is enough information in matrix $H$, it is possible to calculate the parameters that best fit the model and minimize the Least Squares, by first multiplying each side of the equation by the the transpose of $H$:

$$(H^T H) \hat{\theta} = H^T y$$ (6)

which, by inverting the matrix $H^T H$, leads to:

$$\hat{\theta} = (H^T H)^{-1} H^T y$$ (7)

4. Kinematic Models
A key aspect of this work is the translation of the aircraft’s behaviour to a mathematical formula. As the sensors used are very limited, the approximations used to simplify the problem become extremely important, which in the present work resulted in two different kinematic models.

4.1. Model 1
The airspeed of an aircraft can easily be tracked from the "wind triangle" relation, pictured in figure 1, that states that the ground speed vector ($\text{GS}$), at each point, is the sum of the airspeed ($\text{TAS}$) and wind ($\text{W}$) vectors, that is,

$$\text{GS} = \text{TAS} + \text{W}$$ (8)

The GPS is in charge of providing measurements of the ground speed and ground course, while the AHRS of the heading angle.

4.2. Model 2
William Premerlani [13] made an interesting point when analysing the general behaviour of the airspeed during a flight, in a presentation he gave to an air drone community. While the overall theory didn’t get to be duly presented in an official paper, its statements were bold enough to be "dissected" and properly analysed.

The general set-up can be presented as follows: for a flight at a relatively high speed, it can be said that the airspeed will be mainly directed on the longitudinal axis of the aircraft; or in other words, the velocity along the x-axis will be much larger than the other two.

This latest statement is captured in the equation bellow:

$$\text{TAS}^B \approx \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$ (11)

This equation is the result of an approximation, and when subjected to wind gusts or any unexpected behaviour, it may not hold. Still, if these situations are properly identified, this same expression can be a safe assumption at relatively high speeds, except of course, during take-off and landing stages.

Equation 9 is the core of our model, in which we are provided of data from a GPS and AHRS.

In order to insert this model into the algorithm, it was first necessary to be cast in the canonical form of equation 5, defining the observations and parameters to be estimated. Considering an airspace volume over a time interval, and assuming that the airspeed (ensured by the autopilot most of the time) and wind, remain constant within this volume, equation 9 can be applied to a given array of size data of N elements, and manipulating it algebraically results in

$$\begin{pmatrix} \cos(\psi_1 - \chi_1) & \cos(\chi_1) & \sin(\chi_1) \\ \vdots & \vdots & \vdots \\ \cos(\psi_N - \chi_N) & \cos(\chi_N) & \sin(\chi_N) \end{pmatrix} \begin{pmatrix} \text{TAS} \\ W_N \\ W_E \end{pmatrix} = \begin{pmatrix} \text{SpeedEN}_1 \\ \vdots \\ \text{SpeedEN}_N \end{pmatrix}$$ (10)

Expression 10 contains the indication of each matrix when matching the whole expression the LMS canonical form 5. It is simple to distinguish that the parameters to be estimated are exactly the true airspeed of the aircraft, TAS, and both longitudinal components of the wind, $W_N$ and $W_E$, all measured in the NED frame, while the observation matrix is composed by the norm of the longitudinal ground speed, SpeedEN. Matrix H, describing the system, is composed by measurements of ground course angle, $\chi$, and heading angle, $\psi$.

Figure 1: Wind triangle relation.

Assuming a leveled flight, and taking into account the angles of the ground course angle ($\chi$), heading ($\psi$), and wind direction ($\chi_w$), it is also possible to derive the relation,

$$\text{GS}_{xy} = |\text{TAS}| \times \cos(\psi - \chi) + |W| \times \cos(\chi_w - \chi)$$ (9)

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This expression describes the approximation for the airspeed in the body frame, and to be able to work with it in the NED frame, it should be multiplied by the appropriate rotation matrix $R_B^I(\psi, \theta, \phi)$, yielding

$$\text{TAS}^I \approx R_B^I(\phi, \theta, \psi) \times |\text{TAS}|^B.$$ (12)
\[
\overline{\text{TAS}^2} \approx |\overline{\text{TAS}}| \times \begin{bmatrix}
\cos(\psi)\cos(\theta) \\
\cos(\theta)\sin(\psi) \\
-\sin(\theta)
\end{bmatrix}
\] (13)

Vector 13 indicates that the airspeed in the NED frame is approximately the module of the airspeed times the first row of the DCM, that describes the rotation from the body to the inertial frame.

The theoretical model for this situation can thus be described as

\[
\begin{bmatrix}
V_N \\
V_E \\
V_D
\end{bmatrix}
= \begin{bmatrix}
\text{TAS} \times \cos(\psi)\cos(\theta) + W_N \\
\text{TAS} \times \cos(\theta)\sin(\psi) + W_E \\
-\text{TAS} \times \sin(\theta) + W_D
\end{bmatrix}
\] (14)

Just as it for the first scenario, equation 14 had to be formulated in a way it could be incorporated in a Least Squares. Considering an airspace volume over a time interval, and assuming that the airspeed and wind remain constant within this volume, equation 14 can be applied to a given array of size data of N elements, and manipulated into a canonical form of equation 5, resulting in expression 15.

\[

cos(\theta_1)cos(\psi_1) \quad 1 \quad 0 \quad 0 \\
\vdots \quad \vdots \quad \vdots \\
cos(\theta_N)cos(\psi_N) \quad 1 \quad 0 \quad 0 \\
\vdots \quad \vdots \quad \vdots \\
cos(\theta_1)sin(\psi_1) \quad 0 \quad 1 \quad 0 \\
\vdots \quad \vdots \quad \vdots \\
cos(\theta_N)sin(\psi_N) \quad 0 \quad 1 \quad 0 \\
-sin(\phi_1) \quad 0 \quad 0 \quad 1 \\
\vdots \quad \vdots \quad \vdots \\
-sin(\phi_N) \quad 0 \quad 0 \quad 1
\end{bmatrix}
\begin{bmatrix}
H
\end{bmatrix}
= \begin{bmatrix}
V_{N_1} \\
V_{N_2} \\
V_{N_3}
\end{bmatrix}
\] (15)

The major difference when comparing to the first kinematic model is the inclusion of the vertical component of the ground speed along with the pitch angle, resulting directly on the addition of a new parameter, the downward component of the wind.

In expression 15, it is clarified the indication of each matrix when matching the whole expression to the LMS equation 5. The expression is now composed of three main "chunks" of data on both the H matrix, as well as in the y matrix, in which the first N rows are directed to the North component, the second N rows to the East one and the last N rows to the Down one. The new variables, \( V_N \), \( V_E \) and \( V_D \) are the three axis components of the ground course velocity, obtained from a GPS, and the angles of pitch \( \theta \) and yaw \( \psi \) are the attitude angles obtained from the AHRS.

5. Implementation

There are small changes for the general algorithm when considering the two separate models, and the implementation of it presents very specific restrictions. For this reason, it was decided to be used as a back up system to increase the robustness of the already existing standard air data system, and identify if the pitot tube is working as expected.

5.1. Restrictions

For both models the flight data must meet some requirements in order to be validated: The plane should present an approximate horizontal trajectory; the matrix \( H \) should be well conditioned; the acquisition of data should be collected as fast as possible and the mean square error be as low as possible.

The two kinematic models are restricted to an approximate leveled flight, and to quantify the dispersion of altitude measurements in the cluster of data, the first tuning parameter \( \Delta h_{max} \) appears as limited by a maximum altitude rate allowed: \( \Delta h_{max} < \gamma_h \).

Another restriction is the interval of time for the acquisition of data, and a major constrain for this is the wind. As stated before, the wind is a stochastic process, and if not accounting for wind gusts, the only certainty one can have is that for small variations of time, the wind speed should be approximately the same. However, to use the Least Mean Square, it is required a trajectory entropy. That means taking measurements in the order of several seconds, depending strongly on how fast the aircraft can change its attitude. In previous work, C. Hurter et al. [12], used a cluster of data in the order of 1 to 2 hours, and, empirically, experienced engineers back up the fact that the wind varies slowly for the same flight level. Nevertheless, it should be clear that the longer the time order of the cluster, the less accurate will be the results.

The next restriction is defined to quantify how well-conditioned is the matrix \( H \), i.e. to quantify if there is relevant information in the matrix \( H \) to achieve a valid result, and is evaluated through the use of a limited threshold: \( k(H) < \gamma_k \), where \( \gamma_k = 1 \) presents the scenario for which the matrix is best conditioned.

Lastly, the mean square error is taken out using the estimated parameters to appraise the difference between these and the real values. This parameter is also evaluated through the use of a maximum threshold allowed: \( MSE < \gamma_{MSE} \).

5.2. Algorithm

The base algorithm first evaluates the past neighbouring points for a given point \( P \) in time and space, taking into account a time window \( t_1 \), and if all restrictions, previously described, are achieved,
it is allowed to carry on the estimation. If, during an horizontal flight maneuver, there isn’t enough entropy in the measurements to obtain a good estimation, the algorithm rewinds to the start and extends the neighbouring points to a bigger time window $t_2$. This procedure is repeated in loop until the algorithm achieves an estimation, up to a maximum time window $t_{max}$.

If the estimation is not possible at the maximum time window $t_{max}$, for example in the case when the plane starts describing a uniform straight trajectory, the auto-pilot can continue to compare its values obtained from the standard Air Data System with the latest wind estimations as one way to keep the robustness required. This, however, should only be valid for a certain amount of time $time_{hold}$, for which, if outdated, should signal a warning to let the auto-pilot know that the last estimations are no longer valid and it should maneuver the plane to update them when possible.

The back up this system provides can be seen as a "virtual robustness". While continually estimating the parameters, there is a valid way of comparing them with the ones given by the standard ADS, and even in cases where the estimation is not possible, for example in a straight trajectory, as long as the point in time and space of comparison is contained in the $time_{hold}$.

Using the last wind estimation as invariable for the next moments, even if the wind speed does change more than expected comparing with the standard ADS results, the values will still remain in a neighbouring area and are enough to state that the pitot tube is reading good values. However, if the ADS ends up giving enormous errors when comparing with the last wind estimations, it is clear that the pressure sensor is obstructed and at this point, procedures according to each of the users necessities should be done, for example an emergency landing could be deployed.

6. Comparison of models
Using the X-Plane simulator, it was possible to evaluate the algorithm in a controlled environment, more specifically, in three different scenarios:

- Uniform loiter maneuver;
- Variation of wind;
- Slow-varying altitude;

6.0.1 Uniform loiter maneuver
The first interval is an ideal situation, described as having all the required conditions for the algorithm to run: the aircraft is kept at the same height, while it is being maneuvered in a loiter, which secures the necessary entropy on the yaw. Also, the wind components are kept constant.

Figure 3 pictures the results, using the two kinematic models, for Flight 01 in the simulator.

Flowchart 2 depicts the events just mentioned.

![Flowchart of the estimation algorithm](image)

Figure 2: Flowchart of the estimation algorithm.

At first glance, it is possible to notice that, in all variables, there is a closer answer to the real values
using the second kinematic model, even tough there is a clear oscillatory nature of the response. Tables 1 and 2 summarize the mean, standard deviation and absolute maximum values for both implementation errors.

| Kinematic model 1 | Errors | $\mu$ (m/s) | $\sigma$ (m/s) | $|e_{\text{max}}|$ (m/s) |
|-------------------|--------|-------------|----------------|----------------------|
| $e_{\text{TAS}}$  | -0.0054| 0.0827      | 0.3597         |                      |
| $e_{W_N}$         | 0.0833 | 0.0575      | 0.4961         |                      |
| $e_{W_E}$         | -0.0806| 0.0508      | 0.2586         |                      |

Table 1: Statistic values of the errors for model 1.

| Kinematic model 2 | Errors | $\mu$ (m/s) | $\sigma$ (m/s) | $|e_{\text{max}}|$ (m/s) |
|-------------------|--------|-------------|----------------|----------------------|
| $e_{\text{TAS}}$  | 0.0086 | 0.0654      | 0.4348         |                      |
| $e_{W_N}$         | 0.0012 | 0.0950      | 0.1618         |                      |
| $e_{W_E}$         | -0.0473| 0.0989      | 0.1873         |                      |

Table 2: Statistic values of the errors for model 2.

Regarding the airspeed, both models present solutions with similar error statistics, where the mean value is very close to zero, with the standard deviation also very close to one another and a maximum error value justified by the sudden change in the real value at $t = 5450s$.

On the other hand, both wind components have a smaller mean value on the second kinematic model, but also present a higher standard deviation, inherent of the oscillatory response. Furthermore, the maximum values of the error is mitigated in the second model.

6.0.2 Variation of Wind

The scenario in which there is a clear change of the wind, for the same leveled flight, is pictured in Figure 4, where in the time frame $t \in [5000s, 6000s]$, it describes the estimations, moments before, during, and after the transition of wind value. As a way to analyse this situation, the aircraft performed a loiter maneuver, at a constant yaw rate, to secure the estimations.

At about $t = 5545$ there is a change in the wind components, that lasts about 50s until it stagnates for the rest of the flight. Before this transition, both models correctly identify all parameters, while clearly noticing the same oscillatory response on the second model. In the transition time frame of 50s there are large errors in all components of the first model, while these are mitigated in the second model. Information regarding mean, standard deviation and absolute maximum values of all parameters errors is presented in Tables 3 and 4.

Continuing on the transition area, the first model presents maximum errors of airspeed, north and east wind speeds much larger on the first model, rather than the second. Besides this, in the given time frame, while all mean, standard deviation, and maximum errors are relatively small, for both models, the second one contains smaller values on all statistical parameters, indicating that the second model has a better follow up response during these situations.

| Kinematic model 1 | Errors | $\mu$ (m/s) | $\sigma$ (m/s) | $|e_{\text{max}}|$ (m/s) |
|-------------------|--------|-------------|----------------|----------------------|
| $e_{\text{TAS}}$  | -0.0691| 0.3336      | 2.157          |                      |
| $e_{W_N}$         | 0.0974 | 0.2248      | 1.558          |                      |
| $e_{W_E}$         | 0.0202 | 0.4759      | 2.558          |                      |

Table 3: Statistic values of the errors, kinematic model 1.

![Figure 4: Algorithm estimates, during a wind variation.](image)
6.0.3 Slow-varying altitude

The final scenario is one of great importance: a slow-varying altitude maneuver. While the system is not designed to run on these situations, it is important to analyze if it can, during small values of the rate of climb. This situation is presented in Figure 5, for both implementations, where there is a loiter maneuver at a constant yaw rate, along with a slow-varying altitude change, at a $\text{RoC} = -1 \text{m/s}$.

Table 4: Statistic values of the errors, kinematic model 2.

| Errors | $\mu$ (m/s) | $\sigma$ (m/s) | $|e_{\text{max}}|$ (m/s) |
|--------|-------------|---------------|-----------------|
| $e_{TAS}$ | -0.0469 | 0.2256 | 0.4475 |
| $e_{W_N}$ | -0.0166 | 0.1192 | 0.5807 |
| $e_{W_E}$ | 0.0601 | 0.4150 | 1.989 |

Table 5: Statistic values of the errors, kinematic model 1.

| Errors | $\mu$ (m/s) | $\sigma$ (m/s) | $|e_{\text{max}}|$ (m/s) |
|--------|-------------|---------------|-----------------|
| $e_{TAS}$ | 0.0166 | 0.1767 | 0.5316 |
| $e_{W_N}$ | -0.0202 | 0.2046 | 1.080 |
| $e_{W_E}$ | -0.0971 | 0.2092 | 1.168 |

Table 6: Statistic values of the errors, kinematic model 2.

When dealing with a change in altitude, one inherent consequence is the variation in the wind components, which is visually noticed by the blue lines in the graphics. Up until $t = 2300$ s, the altitude is continuously changing, and from then on is kept the same.

Tables 5 and 6 comprise information regarding mean, standard deviation and absolute maximum values for the errors of both models. From the graphics it is visually observed that both implementations, on an altitude change, run smoothly, but from the error functions, it is concluded that the second model presents a higher mean for the airspeed and north wind component, while having smaller standard deviations for all parameters together with lower peek errors for both wind components.

Overall, the complexity inherent to the implementation of the second kinematic model on the algorithm doesn’t present enough advantages to be chosen over the first one. In all situations in which, it indicated more satisfying results, the difference in the errors was not utterly big, besides the fact of it adding an oscillatory nature to the response, that could be amplified by the quality of the pitch angle measurements.

7. Experimental Results

Upon validating both models with simulated data, these were tested using real flight data, previously provided by TEKEVER. In this work, a time window of $t_{\text{window}} = 360$ s was found to be a value large enough to collect data and at the same time, small enough to hold wind values more or less constant. For this reason, this value was used as $t_{\text{max}}$ in the execution of the program.

Also, regarding the tuning parameters, the val-
ues of $k(H) = 10$, $MSE = 1m/s$, and $h_v = 2m/s$, were tuned empirically,  
considering them as standard values. Figure 6 depicts the observed values  
of the airspeed, north and east wind speeds, by the standard ADS, and the estimated values through  
the use of the algorithm here presented. Following right after, it is pictured the residuals associated  
in Figure 7 and statistical data of the residuals in Table 7.

The flight tested represents a flight of recon,  
described by a huge amount of time spent in a loiter  
stage. For this reason, it was found relevant to be  
analysed at its loiter extent.

From $t = 1000s$ up to $t = 9000s$, this flight  
contains the necessary conditions to provide esti-  
mations, and both models are able to identify the  
maneuver. The first kinematic model implementation  
describes a good response follow up in all  
three components, with a mean residual of the air-  
speed at $r_{TAS} = -7.7989m/s$, and the wind field  
with $r_{WN} = 0.3370m/s$ and $r_{WE} = 0.5913m/s$.  
The second model, however, while providing smaller  

![Figure 6: Flight 01 experimental outcome.](image)

![Figure 7: Flight 01 residuals.](image)

| Residuals  | $\mu(m/s)$ | $\sigma(m/s)$ | $|r_{max}|(m/s)$ | $\mu(m/s)$ | $\sigma(m/s)$ | $|r_{max}|(m/s)$ |
|------------|------------|---------------|----------------|------------|---------------|----------------|
| $r_{TAS}$  | -0.7989    | 0.4889        | 2.4060         | -0.1671    | 0.4975        | 2.0301         |
| $r_{WN}$   | 0.3370     | 0.3870        | 1.3040         | 0.2452     | 1.0741        | 2.3912         |
| $r_{WE}$   | 0.5913     | 0.4591        | 1.7230         | 0.8381     | 1.4012        | 3.3742         |

Table 7: Flight 01’s statistic values of the residuals.
mean residuals in the airspeed, and the north component of the wind, depicts larger standard deviations in all parameters, besides the fact of it being unable to be executed in the full time period. These two downsides are explained by the oscillatory behaviour of the response that, as observed in the figures, is intensified in time, specially in the north component of the wind.

Nevertheless, when implementing both models in the algorithm, the parameters are successfully estimated, as expected.

8. Conclusions
The work presented in this document was motivated by a growing necessity to find alternative methods able to replace conventional sensors. Most systems take use of a classic Extended Kalman Filter, or other derived Kalman filters, fusing data from several sensors, as is the case of pitot tubes, GPS, accelerometers, gyroscopes, etc, together with a dynamic model of the aircraft, to estimate in-flight parameters, such as true airspeed, wind speed, angle of attack and sideslip.

The continuous restrictions to have smaller and lighter systems, specially in drones, limits the amount of sensors to be fit in an aircraft, and every system is kept as simple as possible. The true airspeed of the aircraft is a core parameter that depends strongly of pitot tubes sensors, and the main focus of this work was to find an alternative to this sensor, that could provide enough redundancy to the already placed sensors.

From the beginning, this work was a challenge. Besides eliminating completely the pitot tube, it was also presented at a point, that it would be interesting to make a system completely independent of the aircraft as well, since it is known that the attainment of an aircraft’s model is something complex, expensive and time-consuming.

Alongside TEKEVER, there were done some brainstorming ideas that could be put into action, and one of the first was the interpretation of the Parleami’s theory, that was found to be extremely interesting. Later, with the approach of C. Hurter et al. and in discussion with TEKEVER, it was found relevant to also incorporate the Parleami’s theory in the given solution.

With the exclusion of the pitot tubes, wind vanes, and the dynamic model of the aircraft, it was found a way of reaching all the objectives, as long as the aircraft would flight in a way for algorithm to capture its maneuvers.

The work developed in this thesis might still be optimized through the use of several aspects. By using a different modulation of the aircraft’s kinematic, it was shown that it can lead to distinct responses, and by finding a more suitable approximation would directly result in a more satisfying system.

Also, the condition number of the matrix was found to be a good metric of measurements in the cluster data, but it requires a lot of computational effort and by finding an alternative could lead to a significant improvement in the system’s performance.

Lastly, the Least Squares is used as a prime tool to fit the cluster data into the model and estimate the most suitable parameters. Nevertheless, its use also requires a strong computational effort, and an alternative method to analyse the data could also provide an optimal and faster solution to the problem.

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References
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