INDICATED AIRSPEED ESTIMATION FILTER

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Abstract

Indicated Airspeed (IAS) data play a critical role in aircraft flight control, both for pilot and Automatic Flight Control Systems. In unmanned aerial vehicles (UAVs) loss of IAS data could result in loss of aircraft control. This paper addresses the problem of IAS estimation after airdata sensor failure. A complementary filter with cutoff frequency dynamically adapted to flight condition is proposed. The complementary filter produces Airspeed estimation using aircraft attitudes, vertical speed and along heading acceleration. Filter output accuracy has been validated using about 100 hours of flight data at different speeds and altitudes. Comparison between actual flight data and the estimated IAS has shown a good match for all flight conditions, demonstrating the feasibility of using filter output data in case of airdata sensor failure.

LIST OF ACRONYM

IAS: Indicated airspeed
AFCS: Automatic Flight Control System
FCC: Flight Control Computer
UAV: Unmanned Air Vehicle

1. INTRODUCTION

Indicated Airspeed provides information about aircraft speed, as well as makes the pilot aware of proximity to aircraft limits and expected dynamics characteristics. The IAS parameter is a necessary input for AFCS both for flight director modes to maintain the selected cruise speed and for implementation of gains scheduling within control laws.

In case of aircraft equipped with a double redundant pitot-static measurement system, the pilot is responsible to take over control in case of failure of the pitot system. For UAVs loss of IAS data is more critical; this failure certainly leads to abort the mission and it might result in loss of aircraft control. Adding a third redundant sensor system on UAV's is not always feasible, due to installation and weight constraints [1, 2].

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In this paper a reliable method to estimate IAS data on unmanned rotorcraft is presented. Several solutions have been proposed for fixed wing aircraft [1–4], but they are not well applicable for rotorcraft applications due to the different a/c dynamics and airspeed operative ranges.

The solution presented is based on two different elements: the first one is an interpolator, trained offline over available flight data and able to produce an accurate estimate for low frequencies (below 0.1 Hz), while the second element is a IAS estimator using vehicle inertial acceleration to produce an accurate estimate during dynamic maneuvers (above 0.1 Hz).

A complementary filter is used to combine the outputs of the two estimators; these class of filters are widely used in flight control system applications [5–10]. The proposed filter has a variable time constant that implements a dynamic weighting mechanism of one estimate element over the other to optimize overall estimate accuracy [10, 11].

The algorithm has been validated using about 100 hours of flight data in different flight conditions: steady flight, accelerations, climb/descend maneuvers and turns at different speeds and altitudes.

2. IAS ESTIMATION VIA INTERPOLATION FUNCTION

The IAS estimation is mainly based on the following assumption: in forward flight (neglecting atmospheric disturbances) at a fixed pitch angle (θ) the aircraft reaches a specific IAS trim condition, the pitch angle and the IAS are related by the function (1) (see [12]).

(1)
$$\begin{cases} \dfrac{W}{g}\dot{u} = -W\theta\cos(\tau_C) + \Delta X \\ \dfrac{W}{g}\dot{w} = -W\theta\sin(\tau_C) + \Delta Z \qquad \Longrightarrow \quad u \quad = \bar{f}(\theta, \tau_C) = \\ B\ddot{\theta} = \Delta M \qquad\qquad\qquad\qquad\qquad\qquad = f(\theta, w) \end{cases}$$

Where the ΔX, ΔY, ΔM are the aerodynamic force and moment increments, W is the A/C weight, τ_C is the

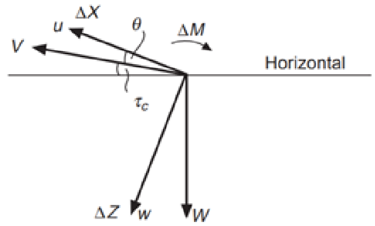

Figure 1. Longitudinal force components in longitudinal plane

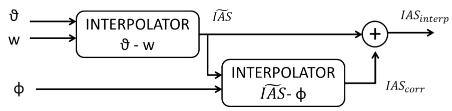

Figure 2. Interpolation algorithm

climb angle, u is the airspeed value and w is the rotorcraft vertical velocity.

It is possible to implement a function $f(\theta, w)$ that accurately fits the real one and produce IAS estimate using pitch attitude data.

The previous equation is valid only for forward flight but it is possible to extend the same concept to other steady flight conditions properly adding the related variables.

Three different types of steady conditions are addressed in this paper: forward flight, climb/descend maneuvers and turns. For these conditions IAS is reasonably related to θ, w and ϕ, where ϕ is the aircraft roll angle:

$$IAS = f(\theta, w, \phi) \tag{2}$$

In the estimation algorithm f is calculated using a least square polynomial regression method in 3 dependent variables, as presented in [13, 14]. To further simplify the computation and to reduce CPU throughput a succession of two variable interpolations has been implemented.

The algorithm has been divided in two different sections (see 2 - Interpolation in the longitudinal-vertical plane using pitch angle θ and vertical speed w - Correction of the IAS first estimation using the roll angle ϕ

Despite the simplicity of this interpolation technique, a significant amount of flight data is needed to minimize interpolation error. The calibration has to be carried out on the target rotorcraft and repeated in case of aerodynamic changes.

3. IAS ESTIMATION VIA INERTIAL INTEGRATION

The IAS estimation via interpolator function presented in the previous section provides good results for quasi-steady flight condition: e.g. during a turn maneuver the speed is correctly estimated once the A/C reaches a constant rate of turn, but the interpolation technique fails on the transition between forward flight and the turn maneuver.

To overcome this problem a dynamic estimation of the IAS has been introduced, integrating the along heading acceleration n_x^{ah} (acceleration projected in the same axis of the pitot probe). The n_x^{ah} is a parameter provided by AHRS and it is usually a noisy parameter. For this reason a second order Butterworth filter has been used to smooth the data before the integration. The estimation of the dynamic IAS is shown in (3):

$$IAS_{dyn} = \frac{1}{s} \cdot \frac{\omega^2}{s^2 + 2\xi\omega + \omega^2} \cdot n_x^{ah} \tag{3}$$

The initial condition of the integrator has to be set as the last valid speed measured before airspeed data loss, which is the starting point of the integration process.

The proposed approach gives reliable estimation of the IAS dynamic variation but the inertial integration is usually affected by drift over time. The main advantage of the integration technique w.r.t. to the interpolation one is that it is not depending on rotorcraft platform.

4. ADAPTIVE COMPLEMENTARY FILTER

To overcome the cons of the two methods presented, a complementary filter can be used. It is mathematically expressed as (4) and (5).

$$y = G_1(s) \cdot u_1 + G_2(s) \cdot u_2 \tag{4}$$

where

$$G_1(s) + G_2(s) = 1 \tag{5}$$

The complementary filter is used to combine the IAS estimated with the two methods described in the previous sections. As previously stated the interpolation is most effective in the quasi-steady flight condition, where the data variation is low or vary with low speed (Equation (6)), while the estimation through integration is valid for dynamic flight conditions where the variations of the data are faster. (Equation (7))

$$u_1 = IAS_{trim} = \bar{f}(\theta, w, \phi) \tag{6}$$

$$u_2 = IAS_{dyn} = \frac{1}{s} \cdot \frac{\omega^2}{s^2 + 2\xi\omega + \omega^2} \cdot n_x^{ah} \tag{7}$$

The design of a complementary filter requires the definition of the cutoff frequency (ω_{CF}). This characteristic

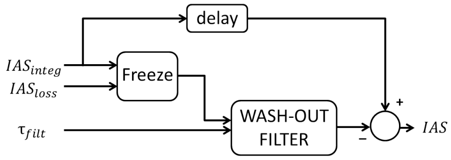

Figure 3. Offset correction algorithm

makes this filtering technique not suitable for this specific application, since the accuracy of the two estimation elements vary with the flight conditions.

In order to solve this problem an adaptive complementary filter is designed; the filter time constant ($\tau_{CF} = \frac{1}{\omega_{CF}}$) is adapted over time, in order to weight more the inertial integration during dynamic maneuvers with respect to the interpolation and vice-versa during steady state conditions. [11] suggest to use fuzzy logic to change the filter time constant, however in this paper a classic boolean logic is deployed for its simplicity, reliability and very low computational cost.

Table I reports the data used to identify the flight condition: for each of the parameter listed a dedicated threshold has been set.

Data	**Description**
θ [deg UP]	Pitch angle
q [deg/s UP]	Pitch rate
ϕ [deg RH]	Roll angle
p [deg/s RH]	Roll rate
w [ft/min UP]	Vertical speed
n_x^{ah} [G]	Acceleration along heading
u/IAS_e [Kts]	Estimated Indicated Airspeed

Table I.

4.1. Offset correction

The offset present at the instant when IAS data loss is detected is subtracted from the high pass filtered data. The offset correction is filtered with a wash out filter, with the same time constant of the complementary filter, in order to eliminate its effect when the complementary filter is fully initialized. Figure 3 summarizes the offset correction logic.

5. RESULTS

The validation of the estimation algorithm has been carried out comparing IAS estimate with the actual IAS data measured by the air data unit in flight; the comparison is shown in the following figure (figure 5). As shown in figure 4 several maneuvers were carried out during the flight.

Approximately 100 flight hours have been analyzed in order to validate the IAS estimation filter. The results are summarized in table II. As highlighted in the table II the estimation of the algorithm is adequate for about 80% of the flight time, the accuracy decreases only for not steady flight condition as vertical climb and sudden accelerations (marked as #A and #B in figure 4)

6. CONCLUSIONS

The paper proposes a technique for airspeed data estimation using inertial data, with the purpose of using estimated data for rotorcraft control in case of airdata sensor failure.

The estimated IAS can also be used to implement a voting mechanism in duplex ADU configurations in case of discrepancy between airdata.

Two different estimation elements have been adopted; the first one is based on the interpolation of attitudes and vertical speed data and produces reliable estimate in steady flight conditions, while the second one is based on the integration of along heading acceleration and produces reliable estimate during dynamic maneuvers.

The data obtained by two different estimators are combined using an adaptive complementary filter: the low frequency input of the filter is the data obtained from the interpolation function while the high frequency input is the integration of the along heading acceleration. The filter time constant is adapted to the flight condition by means of an embedded threshold logic to optimize estimate accuracy.

Comparison with flight data demonstrate that the proposed algorithm produces a reliable and accurate estimate both in steady flight condition and during dynamic maneuvers. Compared with other IAS estimation techniques, the proposed algorithm relies neither on the knowledge of the aircraft model (or its parameters) nor on Kalman filters (usually with high computational cost). The weak point of the proposed methodology lies in the significant amount of airdata required for the design of the low-frequency estimator.

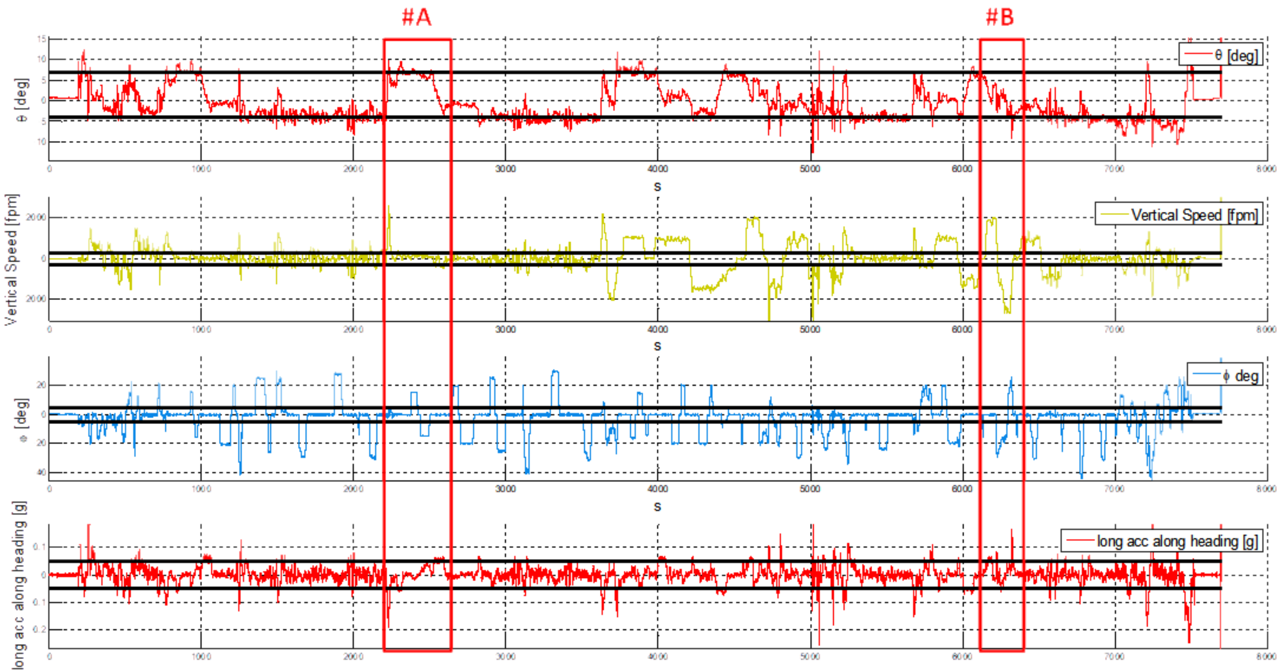

Figure 4. Flight data used for test

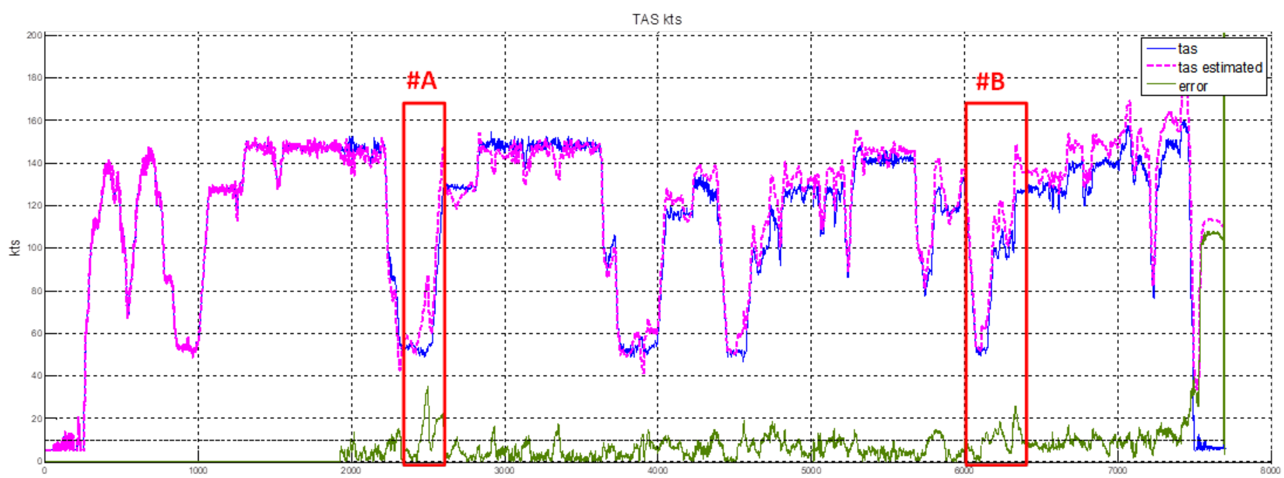

Figure 5. Comparison among real and estimated airspeed

Error	$error < 10kts$	$10kts < error < 20kts$	$error > 20kts$
Estimation Level	**ADEQUATE**	**ACCEPTABLE**	**NOT ACCEPTABLE**
% Time	78.8%	23.6%	5.6%

Table II.

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