

Experimental Evaluation of Two Pitot Free Analytical Redundancy Techniques for the Estimation of the Airspeed of an UAV

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ABSTRACT

A measurement device that is extremely important for Unmanned Aerial Vehicle (UAV) guidance and control purposes is the airspeed sensor. As the parameters of feedback control laws are conventionally scheduled as a function of airspeed, an incorrect reading (e.g. due to a sensor fault) of the Pitot-static tube could induce an incorrect feedback control action, potentially leading to the loss of control of the UAV. The objective of this study is to establish the accuracy and reliability of the two airspeed estimation techniques for eventual use as the basis for real-time fault detection of anomalies occurring on the Pitot-static tube sensor. The first approach is based on an Extended Kalman Filter (EKF) and the second approach is based on Least Squares (LS) modeling. The EKF technique utilizes nonlinear kinematic relations between GPS, Inertial Measurement Unit and Air Data System signals and has the advantage of independence from knowledge of the aircraft model. The LS method is based on explicit knowledge of the aircraft model and has the advantage of on-line computation of the airspeed estimate, with minimal computational effort. The performance analysis was carried out with flight data from the WVU YF-22 UAV research platform. The results of the analysis indicate that the two methods provide essentially comparable performance in terms of mean (~ 1 m/s) and standard deviation (~ 1.5 m/s) of the airspeed estimation error which is about the 5% of the mean in-flight velocity of 32 m/s.

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INTRODUCTION

A measurement device that is extremely important for UAV guidance and control purposes is the airspeed sensor. As the parameters of Unmanned Aerial Vehicle (UAV) feedback control laws are typically scheduled as a function of the airspeed, an incorrect reading (e.g. due to a sensor fault) of the Pitot tube could induce an incorrect feedback control action, potentially leading to the loss of control of the UAV. The criticality of this class of failure was brought to the forefront of the flight control community after the results of the investigations of the crash of the Air France Airbus A330 (Flight

447) in June 2009 were made available to the aviation community [1]. Other relevant findings can be found also in [2, 3]. In the context of Analytical Redundancy (AR) based Sensor Fault Detection Isolation and Accommodation (SFDIA) [4, 5, 6, 7, 8], the development of reliable models ("virtual sensors") to be employed within the SFDIA scheme in lieu of possibly faulty physical sensors is very critical. In fact there is today a significant interest in the development of alternative schemes for deriving real-time airspeed information without the direct use of Pitot-static tube information.

In [9, 10] the so called two and three vector geometric approaches were proposed to estimate the wind speed and airspeed from successive measurements from Global Positioning System (GPS) via Least Square (LS) optimization. In [11] a direct method based on the measurements of body axis acceleration is proposed to infer the wind velocity and airspeed information. In [12] an Extended Kalman Filter (EKF) approach is proposed to estimate the wind field from the fusion of GPS and Pitot-static tube measurements. Similarly, in [13] three alternative estimation methods are proposed to provide model based estimation of the airspeed. The above mentioned models are mainly oriented toward the estimation of the local wind field experienced by the aircraft and rely directly or indirectly on the Pitot signal itself and for this reason are not very suitable for the SFDIA purposes where a completely independent estimation of the airspeed is preferable.

In this paper, relying on previous works proposed in [14], the authors compare two approaches for Pitot-static tube airspeed estimation that do not make a direct use of the Pitot airspeed signal in the estimation. The purpose of the study is to assess the accuracy of the proposed airspeed estimation techniques that can be used for real-time fault detection of anomalies occurring on the Pitot tube sensor or as a "virtual sensor" at post failure conditions.

The first estimation technique is based on an Extended Kalman Filter (EKF) [15] that utilizes the nonlinear kinematic relations between GPS, Inertial Measurement Unit (IMU) and Air Data System (ADS) signals. The advantage of this method is the independence from the knowledge of the aircraft modeling parameter. The only source of uncertainty expected for this formulation is the inaccuracies and noise due to the practical measurements from GPS, IMU and ADS sensors. The disadvantage is the need of estimating explicitly the wind speed that relates the airspeed to ground speed and the need of tuning the EKF process and measurement noise covariance matrices.

The second method relies on explicit modeling information of the aircraft, in which the estimation is based on the identification of the aerodynamic, geometrical and inertial parameters involved in the angle of attack dynamics equation. Specifically, assuming that all the sensors on the UAV are fully functional except the airspeed sensor and assuming the aerodynamic model proposed in [16, 17], it can be shown that the resulting dynamic equation is quadratic in the airspeed signal $V(t)$ the parameters of which can be identified offline from a set of recorded flight data; therefore, this equation can be solved online assuming that all the involved coefficients and relative measurements are known, to estimate the airspeed. The advantage of this method is its simplicity (only one equation) while the disadvantage is the need of the offline identification of the modeling parameters, and that need of a periodical retuning.

A detailed performance comparison of the two airspeed estimation methods was carried out based on 4 flights data records of the West Virginia University YF-22 scale model [18].

THE EKF ESTIMATION MODEL (APPROACH #1)

The EKF approach considers the estimation of aircraft body-axis velocity components (u, v, w) , Euler attitude angles, (ϕ, θ, ψ) , and three-axis wind velocity components, (μ_x, μ_y, μ_z) in Earth-fixed axes. This estimation is performed through the functional fusion of Inertial Measurement Unit (IMU) measurements of three-axis accelerations (a_x, a_y, a_z) , angular rates (p, q, r) , Global Positioning System (GPS) velocity components (V_x, V_y, V_z) , and wind vane measurements of angle of attack (α) and sideslip (β) . The relation between the GPS and wind velocity expressed in the Earth-fixed axes and the body-axis velocities is given by the following reference frame transformation [16]

$$\begin{bmatrix} u \\ v \\ w \end{bmatrix} = DCM^T \left(\begin{bmatrix} V_x \\ V_y \\ V_z \end{bmatrix} - \begin{bmatrix} \mu_x \\ \mu_y \\ \mu_z \end{bmatrix} \right) \quad (1)$$

where DCM is the Direction Cosine Matrix between the body-axes and Earth-fixed axes, which is defined by successive rotations of the roll, pitch, and yaw angles (ϕ, θ, ψ) of the aircraft and is defined as follows

$$DCM = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi & \cos\phi \end{bmatrix} \quad (2)$$

The dynamic equations for the three body-axis velocity states are then given by [16]:

$$\begin{bmatrix} \dot{u} \\ \dot{v} \\ \dot{w} \end{bmatrix} = \begin{bmatrix} 0 & -w & v \\ w & 0 & -u \\ -v & u & 0 \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix} + DCM^T \left(\begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix} - \begin{bmatrix} \dot{\mu}_x \\ \dot{\mu}_y \\ \dot{\mu}_z \end{bmatrix} \right) + \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} \quad (3)$$

where 'g' is the acceleration due to gravity. The dynamic equations for the three attitude angles is given by [15]

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi \tan\theta & \cos\phi \tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi \sec\theta & \cos\phi \sec\theta \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix} \quad (4)$$

Due to the random nature of wind, e.g. turbulence, it is challenging to predict the behavior of the local wind field dynamics. Therefore, the wind velocity state dynamics are modeled as a random walk process:

$$\begin{bmatrix} \dot{\mu}_x & \dot{\mu}_y & \dot{\mu}_z \end{bmatrix}^T = \mathbf{w}_\mu \quad (5)$$

where $\mathbf{w}_\mu$ denotes a zero-mean Gaussian process noise vector associated with the components of wind accelerations.

Grouping together equations (3) (4) and (5) it is possible to express the overall dynamics in the standard form

$\dot{X}(t) = f_c(X(t), U(t))$ where $X = [u, v, w, \phi, \theta, \psi, \mu_x, \mu_y, \mu_z]$ is the state vector and $U = [a_x, a_y, a_z, p, q, r]$ is the input vector. The observation vector is given by the 3 GPS velocity components and by the true angle of attack and sideslip, that is $Y = [V_x, V_y, V_z, \alpha, \beta]$. The components of the nonlinear observation function $Y(t) = h(X(t), U(t))$ expressed as function of the state space variables are [16]

$$\begin{bmatrix} V_x \\ V_y \\ V_z \end{bmatrix} = DCM \begin{bmatrix} u \\ v \\ w \end{bmatrix} + \begin{bmatrix} \mu_x \\ \mu_y \\ \mu_z \end{bmatrix} \quad (6)$$

$$\alpha = \tan^{-1}\left(\frac{w}{u}\right) \quad \beta = \sin^{-1}\left(\frac{v}{\sqrt{u^2 + v^2 + w^2}}\right) \quad (7)$$

where (6) descends immediately from the definition (1) and (7) descends from the definition the aerodynamics angles [16].

NOTE: An important feature of the above EKF estimation model is that it is based entirely on first principle kinematic and dynamic equations and sensor readings, therefore it does not contain any aircraft modeling errors; i.e. the equations do not depend on inertial, aerodynamic, or geometric parameters. The only uncertainty to be expected in this model is due the inaccuracies associated to the measurements from the accelerometers, rate gyroscopes, GPS and ADS sensors. For this reason this formulation of airspeed estimation is general and therefore can be applied to any fixed-wing aircraft as long as it is instrumented with the necessary sensors, i.e. IMU, GPS, and relative wind vanes.

Model Discretization

Since the flight computer provides measurements at discrete times at a rate of 50 Hz (sampling time $T_s=0.02$) a discrete time EKF was implemented in this study. As the 9 state equations in (3, 4, 5) are given in a continuous-time form

$\dot{X}(t) = f_c(X(t), U(t))$, for the implementation of the EKF in discrete time it requires a discretization. A first order discretization of the nonlinear function $f_c(X(t), U(t))$ was used leading to the model

$$X_k = X_{k-1} + T_s f_c(X_{k-1}, U_k) \triangleq f(X_{k-1}, U_k) \quad (8)$$

where $X_k = X(kT_s)$, $U_k = U(kT_s)$ and $Y_k = Y(kT_s)$. The resulting discrete time model with the addition of state and measurement noise is

$$\begin{aligned} X_k &= f(X_{k-1}, U_k) + N_x \\ Y_k &= h(X_k, U_k) + N_y \end{aligned} \quad (9)$$

In (9) the vector $N_x = [N_{u'}, N_{v'}, N_{w'}, N_{\phi'}, N_{\theta'}, N_{\psi'}, N_{\mu_x'}, N_{\mu_y'}, N_{\mu_z'}]^T$ is a Gaussian zero-mean process noise with covariance matrix $Q = E[N_x N_x^T]$; $N_y = [N_{V_x'}, N_{V_y'}, N_{V_z'}, N_{\alpha'}, N_{\beta'}]^T$ is a Gaussian zero-mean measurement white noise with covariance matrix $R = E[N_y N_y^T]$. Further it is assumed that process and measurement noise are independent that is $E[N_x N_y^T] = 0$. The estimation of the amplitude of the airspeed is immediately computed from the EKF body axis velocities, that is:

$$V_{EKF}(k) = (u^2(k) + v^2(k) + w^2(k))^{0.5} \quad (10)$$

Similarly, the estimation of magnitude of the local wind is computed from the three EKF wind states as follows:

$$V_{WIND}(k) = (\mu_x^2(k) + \mu_y^2(k) + \mu_z^2(k))^{0.5} \quad (11)$$

The EKF Algorithm

Based on the nonlinear discrete time model (9) a standard EKF algorithm was implemented [15] as follows.

Prediction step

$$\begin{aligned} \hat{X}_{k/k-1} &= f(\hat{X}_{k-1/k-1}, U_k) \\ P_{k/k-1} &= A_k P_{k-1/k-1} A_k^T + Q \end{aligned} \quad (12)$$

where A_k is the Jacobian of vector function f^* with respect to $X_{k-1/k-1}$ and $Q = E[N_x N_x^T]$.

Correction step

$$\begin{aligned} \hat{Y}_k &= h(\hat{X}_{k/k-1}, U_k) \\ K_k &= P_{k/k-1} H_k^T (H_k P_{k/k-1} H_k^T + R)^{-1} \end{aligned} \quad (13)$$

where H_k is the Jacobian of observation vector function h^* with respect to $X_{k/k-1}$ and K_k is the Kalman gain matrix that is used to correct the state prediction and the error covariance matrix: