Calibration of Aircraft Airdata Systems Using Adaptive Filtering Algorithm

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Abstract. This paper focuses on the calibration of aircraft airdata system to obtain online accurate Angle of Attack (AOA) and Angle of Sideslip (AOSS) from measured quantities contain error. For this purpose, an adaptive version of the extended Kalman filter (EKF) is employed to estimate accurately flight path trajectories of an aircraft. The investigations are made with flight simulated data with turbulence effects. Results are analyzed and found that adaptive EKF provides more accurate results over EKF.

1 Introduction

Calibration of aircraft airdata system is referred to the reconstruction of measured trajectories accurately from measured air data contain error. Typical airdata system of aircraft contains the sensors of pitot tubes with vanes and pressure probes. Precise knowledge of Angle of Attack (AOA) and Angle of Sideslip (AOSS) is essential for many flight applications such as in-flight simulation, aircraft modeling and model following control [1][2]. In the flight control architecture, AOA and AOSS are used as feedback control signals and hence accurate information of flow angles are crucial for unstable fighter aircraft. Moreover, transport aircraft also requires the accurate value of AOA for the stall warning system (SWS) for the safe operation of flight.

The airdata measurement is solely dependent on the data from the sensors installed on the aircraft and such sensor data are prone to errors during the time of measurement due to the flow distortion at aircraft body and the sensors misalignment. Multiple sensors are placed at different points of an aircraft based on the minimum variation of static pressure across the aircraft geometry for the accurate measurements of the same quantity of airdata. The errors caused by the pressure field and by flow angularity are called position errors and it will introduce variation in readings of the measurand. For accounting those errors, flow distortion effect is taken into the consideration by wind tunnel testing with use of the scaled version of the aircraft, and resulting correction part to the flight measurement is called as position error correction [3]. Nevertheless, there may be errors in such a correction process due to the scaled version of the aircraft and calm testing environment equivalent to ideal condition of an atmosphere which is not the case in actual flight. Moreover, these airdata measurements are influenced by several flight variables that may vary over a very wide range; thus, airdata sensors calibration must be treated as multidimensional and nonlinear problem [4]. To this end, online aircraft modeling method has attracted more and more research attention for the design of adaptive controller to maintain flight stability and high performance in uncertain environment where, both process and measurement noise occur [5], [6].

Measured flight data can contain a considerable amount of noise. Moreover, there might be biases and unobserved states in the system model which must be estimated by using filtering techniques. The most popular nonlinear filtering technique is the extended Kalman filter (EKF) [7]. Although EKF is
widely used, proper knowledge of its noise characteristics is necessary, failing of this might lead to divergence of the filter. To avoid these problems, an adaptive extended Kalman filter might be applied, which automatically tunes the filter noise covariance matrices $Q$ and $R$ to adapt insufficiently known prior values. There have been many investigations in the area of adaptive filter and parameter estimation algorithm [8-12].

The calibration of aircraft airdata system can be viewed as state and estimation problem of flight path reconstruction (FPR) [2]. The main goal of the investigation is to obtain online accurate estimates of AOA and AOSS from the flight measurements. For this, we have proposed an adaptive filtering algorithm to obtain accurate estimates of Angle-of-Attack (AOA) and Angle-of-Sideslip (AOSS) in real time. The special attention for the presence of turbulence during the flight maneuvers is considered through the flight simulation and estimated its flight path trajectories as an aircraft gets affected by the adverse effect of atmospheric disturbance. The approach used for the adaptive version is based on estimating the covariance of the process (system dynamics) and measurement noises for this estimation problem by using the covariance matching technique [2]. Therefore, the proposed adaptive filter to estimate aircraft flow angles is needed to be derived from the covariance matching technique, by employing filter residuals to adjust the noise statistical properties. The proposed adaptive filter composed of an extended Kalman filter [12] as the main filter and two parallel Kalman filters for estimating main filter process noise statistics. By estimating the process and measurement noise covariance, the proposed algorithm will be able to compensate the estimation errors resulting from the insufficient knowledge of noise statistics in the estimation problem. The main contributions of this paper are

1. The investigation of calibration of aircraft airdata system has been carried out with the simulated data of a fighter aircraft in the presence of turbulence. Adaptive version of extended Kalman filter is used for this purpose.
2. The estimated results are compared with the estimates obtained from the extended Kalman filter and true value to demonstrate the efficacy of the proposed approach of Adaptive EKF.

The rest of the paper is organized as follows. Section 2 presents the problem formulation for the calibration of aircraft airdata system, and adaptive version of extended Kalman filter is described in section 3 in detail. The estimation results from simulated data are given in section 4 with discussion. Section 5 describes concluding remarks of the paper.

### 2 Problem formulation

For the reconstruction of measured trajectories from noisy airdata, aircraft dynamics is represented by the first order differential equation as follows [13]:

$$
\begin{align*}
\dot{u} &= -(p_u - \Delta p)w + (p_r - \Delta r)v - g \sin \theta A_u; \quad u(t_0) = u_0 \\
\dot{v} &= -(r_u - \Delta r)u + (p_u - \Delta p)w - g \cos \phi \sin \theta A_v; \quad v(t_0) = v_0 \\
\dot{w} &= -(p_r - \Delta r)w + (p_u - \Delta p)u - g \cos \phi \sin \theta A_w; \quad w(t_0) = w_0 \\
\dot{\phi} &= -(p_u - \Delta p)\sin \phi \tan \theta + (r_u - \Delta r)\cos \phi \tan \theta; \quad \phi(t_0) = \phi_0 \\
\dot{\theta} &= -(q_u - \Delta q)\cos \phi \tan \theta + (q_r - \Delta r)\tan \phi; \quad \theta(t_0) = \theta_0 \\
\dot{h} &= u \sin \theta - v \sin \phi \cos \theta - w \cos \phi \cos \theta; \quad h(t_0) = h_0
\end{align*}
$$

(1)

where $p$, $q$ and $r$ are the projection of the angular rate vector along the aircraft body axis and their biases in measurements are defined by $(\Delta p, \Delta q, \Delta r)$; $\theta$ and $\phi$ are the pitch and the roll angles respectively; $u$, $v$, $w$ are inertial speed projections along the aircraft body axis. The linear accelerations $(A_u, A_v, A_w)$ at the centre of gravity are computed from the accelerations measured by the accelerometer at a point away from the centre of gravity of an aircraft [1]. The state trajectories $u, v, w, \phi, \theta, h$ of aircraft dynamics in (1) can be reconstructed from the following measurement equation:
\[
V_w = \sqrt{u^2 + v^2 + w^2} + \eta_v
\]
\[
\bar{q}_w = 0.5\rho\left(u^2 + v^2 + w^2\right) + \Delta\bar{q} + \eta_q
\]
\[
\phi_w = \phi + \eta_\phi
\]
\[
\theta_w = \theta + \eta_\theta
\]
\[
h_w = h + \eta_h
\]
\[
\alpha_w = K_\alpha \tan^{-1}\left(\frac{w}{u}\right) + \Delta\alpha + \eta_\alpha
\]
\[
\beta_w = K_\beta \sin^{-1}\left(\frac{v}{\sqrt{u^2 + v^2 + w^2}}\right) + \Delta\beta + \eta_\beta
\]

where \( \eta \) is associated additive measurement noise. The density of air \( \rho \) can be computed from the actual measurement of static pressure \( P_s \) using universal gas law \( \rho = \frac{P_s}{RT_s} \). \( R \) is the gas constant and \( T_s \) the static temperature \( K_\alpha \) and \( K_\beta \) are the scale factors, and \( \Delta\alpha, \Delta\beta \) are the biases used to model the measurement errors in (2). These are the sensor calibration parameters obtained by estimation. The sensor offset corrections for the flow angles measurements can be done through computation of the velocity components along the three body-fixed axes at an off centre of gravity location from \( u, v \) and \( w \). We can compute the AOA and AOS from the reconstructed trajectories of \( u, v, w \) as follows [12]:

\[
\alpha = \tan^{-1}\left(\frac{w}{u}\right) \quad \text{and} \quad \beta = \sin^{-1}\left(\frac{v}{\sqrt{u^2 + v^2 + w^2}}\right)
\]

By taking the state \( x = [u, v, w, \phi, \theta, h]^T \in \mathbb{R}^6 \), input \( u_m = [A_x, A_y, A_z, p, q, r]^T \in \mathbb{R}^6 \), measurement \( z = [V_m, \bar{q}_m, \phi_m, \theta_m, h_m, \alpha_m, \beta_m]^T \in \mathbb{R}^7 \) and parameter \( \Theta = [\Delta\rho, \Delta q, \Delta r, \Delta A_x, \Delta A_y, \Delta A_z, \Delta\bar{q}, K_\alpha, \Delta\alpha, K_\beta, \Delta\beta] \in \mathbb{R}^{11} \), the postulated aircraft system dynamics in (2) and (3) can be described by the following continuous-discrete state space model:

\[
\dot{x}(t) = f\left[x(t), u_m(t), \Theta, w(t)\right]; x(t_0) = x_0
\]
\[
y(t) = h[x(t), \Theta]
\]
\[
z(k) = y(k) + \eta(k), k = 1, 2, \ldots, N
\]

where \( f \) and \( h \) are the general non linear functions. The measurement vector \( z \) is sampled at \( N \) discrete time steps with a fixed sampling time \( \Delta t \) and \( k \) is the discrete time index. The measurement noise vector \( \eta(k) \) in (4) is assumed to be a sequence of independent zero mean white Gaussian noise with covariance matrix \( R \), and \( w(t) \) represents the noise in measured inputs \( u_m \) with covariance matrix \( Q \). As a result, the estimation of aircraft airdata system can be viewed as state and parameter estimation problem for the reconstruction of flight path trajectories. The constant sensor parameters \( \Theta \) can be considered as output of an auxiliary dynamic system presented in (5)

\[
\dot{\Theta} = 0
\]

This dual estimation problem can be further reduced into a state estimation problem by defining a augmented state vector as:

\[
x_a = \begin{bmatrix} x \\ \Theta \end{bmatrix}
\]

(6) and thus final extended system becomes
\[ x_a = f_a \left[ x_a(t), u_a(t), w(t) \right] \]
\[ y(t) = h_a \left[ x_a(t) \right] \]
\[ z(k) = y(k) + v(k) \tag{7} \]

where the augmented variables are denoted by a subscript 'a'. The most widely used nonlinear estimation algorithm is extended Kalman filter [12], but it is hard to tune the values of noise covariances \( Q \) and \( R \) when dealing with significant noise variations in sensor measurements. To avoid this problem, an adaptive filtering algorithm is proposed to estimate the flight path trajectories.

3 Adaptive filtering algorithm

Introduced adaptive extended Kalman filter (AEKF) consists of main filter as an EKF and two parallel Kalman filters for estimating process and measurement noise covariance matrices for main filter. The block diagram of AEKF is given in Figure 1 and it explains the working of the estimation algorithm without knowing the information of noise covariances. The first parallel filter handles state estimation by the process noise. The residual is estimated from the predicted and corrected states of the main filter, which is given as input to the first parallel filter [14]. For an EKF as a main filter, the linearized system is calculated based on (7) through the following derivatives with the Jacobians defined by:

\[ A(k) = \frac{\partial f_a(x(t), u(t), 0)}{\partial x} \mid \dot{x}(k) \]
\[ B(k) = \frac{\partial f_a(x(t), u(t), 0)}{\partial u} \mid \dot{x}(k) \]
\[ C(k) = \frac{\partial h_a(x(t))}{\partial x} \mid \dot{x}(k) \tag{8} \]

The state transition matrix \( \Phi \) and its integral \( \Psi \) at each discrete point are given by,

\[ \Phi(k+1) = I + A(k)\Delta t + A^2(k)\frac{\Delta t^2}{2!} + \ldots \tag{9} \]
\[ \Psi(k+1) = I\Delta t + A(k)\frac{\Delta t^2}{2!} + A^2(k)\frac{\Delta t^3}{3!} + \ldots \tag{10} \]

By calculating the transition matrix \( \Phi \) and its integral \( \Psi \), the following standard Kalman filter equations of time propagation and measurement correction are used with assumption of initial state and covariance matrix at first [1][15].

\[ \dot{x}(k+1) = \dot{x}(k) + \int_{t_{k+1}}^{t_{k+1}} f(x(t), u_a(t), 0) \, dt \]
\[ \tilde{P}(k+1) = \Phi(k+1) \tilde{P}(k) \Phi^T(k+1) \]
\[ + \Psi(k+1) B(k) Q(k) B^T(k) \Psi^T(k+1) \]
\[ K(k) = \tilde{P} C^T(k) \left[ C(k) \tilde{P}(k) C^T(k) + R(k) \right]^{-1} \tag{11} \]
3.1 Estimation of process noise covariance

The parallel filter determines the mean (MPN) and covariance (CPN) and is fed back to the main filter [16]. Noise dynamics is modeled as a random walk to handle its stochastic nature. The residual constitute part of the parallel filter measurement vector as

$$\hat{x}(k) = \bar{x}(k) + K(k)[z(k) - h(\bar{x}(k))]$$

$$\hat{P}(k) = [I - K(k)C(k)]\hat{P}(k)$$

which is equivalent to,

$$MPN_m(j+1) = \hat{x}(j+1) - \bar{x}(j+1)$$

The associated covariances can be calculated as

$$CPN_m(j) = C_{MPN}(j) - \{\Phi(j)\hat{P}(j-1)\Phi^T(j) - \hat{P}(j)\}$$

(15)

Only diagonal terms from the covariance measurement matrix are considered. A correction is desired to keep covariance matrix positive semi definite, changing negative values into zero. The Eq. (13) and (15) define the measurement model for the first parallel filter. The associated dynamic model to describe process noise is as a random walk, just as it was proposed for wind and for constant parameters in the EKF formulation. Therefore, process noise properties are considered constants with a zero mean white noise additive term.

$$\begin{bmatrix} MPN(j+1) \\ \text{diag} (CPN(j+1)) \end{bmatrix} = \kappa^* \begin{bmatrix} MPN(j) \\ \text{diag} (CPN(j)) \end{bmatrix} + \begin{bmatrix} w21(j) \\ w22(j) \end{bmatrix}$$

(16)

where, 

$$\kappa = \begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix}$$

(17) and

$$w2x(j)$$

is a Gaussian white noise vector with properties

$$w2x(j) \sim N(0, Q2x).$$

Compiling (13) and (15), in a matrix to form the measurement model.
and consequently

\[
\begin{bmatrix}
MPN_j \\
\text{diag}(CPN_j)
\end{bmatrix} = \begin{bmatrix}
\hat{x}(j) - \hat{x}(j) \\
\text{diag}\left(C_{MPN(j)} - \left(\Phi(j)\hat{P}(j-1)\Phi^T(j) - \hat{P}(j)\right)\right)
\end{bmatrix}
\]

(18)

\[
\begin{bmatrix}
MPN_j \\
\text{diag}(CPN_j)
\end{bmatrix} = \kappa^* \begin{bmatrix}
\nu 21(j) \\
\nu 22(j)
\end{bmatrix}
\]

(19)

where \(\nu 2x(j)\) is a Gaussian white noise vector with properties \(\nu 2x(j) \sim N(0, R2x)\). Concluding, (16)(19) compose the first parallel filter dynamic and measurement models respectively.

3.2 Estimation of measurement noise covariance

The second parallel filter is used to estimate the main filter measurement noise statistics on the same basis used in the last section, but now residuals used are innovation. This approach is derived from the covariance matching technique. The innovations should have white noise, zero mean characteristics, and be stationary and time uncorrelated. The main filter measurement noise means MMN and covariance CMN are estimated by considering them as states of second parallel filter.

The measurement of the main filter measurement noise means can be obtained from the innovations as

\[
MMN_m(i) = z(i) - h(\hat{x}(i))
\]

(20)

The innovation covariance matrix can be calculated as

\[
C_{inn}(i) = \left[MMN_m(i) - \bar{MMN}_m(i)\right]\left[MMN_m(i) - \bar{MMN}_m(i)^T\right]
\]

The theoretical innovation variance

\[
H(i)\tilde{P}(i)H(i)^T + R(i)
\]

(21) can be approximated directly by its estimated values as

\[
E[z(i) - h(\hat{x}(i))]z(i) - h(\hat{x}(i)) = H(i)\tilde{P}(i)H(i)^T + R(i)
\]

(22)

Thereby providing a measurement model for the main filter measurement noise covariance matrix

\[
CMN_m(i) = C_{MMN}(i) = H(i)\tilde{P}(i)H(i)^T
\]

(23)

The same procedure described in the last section was adopted here to consider only diagonal elements and to guarantee the positive semi definite property. Negative values are interpreted as low covariance levels and therefore zeroed. The second parallel filter has taken the same consideration regarding the stochastic nature of the problem. The dynamic model is considered as a random walk, that is,

\[
\begin{bmatrix}
MMN(j+1) \\
\text{diag}(CMN(j+1))
\end{bmatrix} = \kappa^* \begin{bmatrix}
MMN(j) \\
\text{diag}(CMN(j))
\end{bmatrix} + \begin{bmatrix}
\nu 31(j) \\
\nu 32(j)
\end{bmatrix}
\]

(24)

where \(\kappa = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\) and \(\nu 3x(j)\) is a Gaussian white noise vector with properties \(\nu 3x \sim N(0, Q3x)\).

grouping equations (20) and (23) in matrix form, we obtain

\[
\begin{bmatrix}
MPN_m(i) \\
\text{diag}(CPN(i))
\end{bmatrix} = \begin{bmatrix}
z(i) - h(\hat{x}(i)) \\
\text{diag}\left(C_{MPN(i)} - H(i)\tilde{P}(i)H(i)^T\right)
\end{bmatrix}
\]

(25) and

\[
\begin{bmatrix}
MPN_m(i) \\
\text{diag}(CPN(i))
\end{bmatrix} = \kappa^* \begin{bmatrix}
MMN(j) \\
\text{diag}(CMN(i))
\end{bmatrix} + \begin{bmatrix}
\nu 31 \\
\nu 32
\end{bmatrix}
\]

(26)

4 Results and discussions
The proposed adaptive filtering algorithm was applied to the flight simulated data containing turbulence effect. Flight simulation was conducted at the flight conditions of Mach 0.3 and altitude of 1800m for a given rudder pedal input. The effect of turbulence was also incorporated in the simulation. The simulated data were sampled at an interval of 0.025 seconds.

Figure 2. Measured and estimated values for rudder pedal input.

In the estimation model, the dynamical representation of atmospheric turbulence is considered by including Dryden model [17] in addition to the aircraft system equations (1). The features that distinguish one turbulence structure from the other are the turbulence intensity $\sigma$ and integral scale of turbulence $L$.

\[
\begin{align*}
\hat{y}_u &= -y_u + x_u k_u \sqrt{\frac{\pi}{\Delta t}} \\
\hat{y}_{v_2} &= y_{v_2} \\
\hat{y}_v &= -\frac{y_{v_2} - 2y_v}{t_v} + x_v \sqrt{\frac{\pi}{\Delta t}} \\
\hat{y}_{w_2} &= y_{w_2} \\
\hat{y}_w &= -\frac{y_{w_2} - 2y_w}{t_w} + x_w \sqrt{\frac{\pi}{\Delta t}}
\end{align*}
\]

where $x_u, x_v, x_w$ are the random numbers are generated to simulate the random nature of turbulence; $t_u, t_v, t_w, k_u, k_v, k_w$ are the time constants and are defined as:

\[
t_u = L_u / V_t; \quad t_v = L_v / V_t; \quad t_w = L_w / V_t \quad \text{where} \quad V_t = \sqrt{u^2 + v^2 + w^2}, \quad \sigma_u = \sigma_v = \sigma_w = \sigma
\]

and

\[
L_u = L_v = L_w = L, \quad k_u = \sqrt{\frac{2\sigma_u^2 t_u}{\pi}}, \quad k_v = \sqrt{\frac{2\sigma_v^2 t_v}{\pi}}, \quad k_w = \sqrt{\frac{2\sigma_w^2 t_w}{\pi}}
\]
The turbulence in velocity components in flight path axes can now be obtained using the relations [17]

\[ u_{ff} = y_u \]
\[ u_{ff} = \frac{k_v}{t_v} \left( \frac{y_{v2}}{t_v} + \sqrt{3} \cdot y_{v1} \right) \]  
\[ (29) \]
\[ w_{ff} = \frac{k_w}{t_w} \left( \frac{y_{w2}}{t_w} + \sqrt{3} \cdot y_{w1} \right) \]

Turbulence generated in flight path axes transformed to body axes are given by:

\[ \begin{bmatrix} u_{bf} \\ v_{bf} \\ w_{bf} \end{bmatrix} = A_{bf} \begin{bmatrix} u_{bf} \\ v_{bf} \\ w_{bf} \end{bmatrix} \]
\[ A_{bf} = \begin{bmatrix} \cos(\alpha) \cos(\beta) & -\cos(\alpha) \sin(\beta) & -\sin(\alpha) \\ \sin(\beta) & \cos(\alpha) & 0 \\ \sin(\alpha) \cos(\beta) & -\sin(\alpha) \sin(\beta) & \cos(\alpha) \end{bmatrix} \]  
\[ (30) \]

where, \( \beta = \sin^{-1} \left( \frac{V}{V_f} \right) \) and \( \alpha = \tan^{-1} \left( \frac{W}{U} \right) \)

Figure 3 shows that estimated AOSS by adaptive EKF makes more agreement with its true values compared to the estimate obtained from EKF. This illustrates the superiority of proposed Adaptive EKF to calibrate the aircraft airdata system over EKF in the presence of turbulence.

5 Conclusions

An adaptive version of EKF was applied to dynamic maneuvers to calibrate the AOA and AOSS in real time from the simulated data. Simulations in software were carried out with moderate turbulence effects at 1800 meters and 0.3 Mach to obtain sufficient variations in AOA and AOSS of the aircraft. The investigation was made primarily from simulated data with turbulence effects using simulation software, and it was shown that both AOA and AOSS estimates were accurate. It is observed that adaptive EKF is superior to EKF in terms of accuracy of estimation as it uses instantly estimated noise covariance matrices instead of the tuned value of covariance matrices in EKF. Thus, the consistently
good results obtained using adaptive filtering algorithm establish that this approach is great value for online implementation.

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