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SYNTHETIC AIR DATA - A COMPARATIVE PRACTICAL STUDY

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Abstract

Synthetic Air Data Systems are airspeed estimation algorithms. Such algorithms are built using measurements from sensors other than the classical Pitot tubes, from which airspeed estimates can be computed. This paper presents brief discussions over three direct estimation algorithms that use inertial sensors (IRS) and GPS as sources of information. It is also proposed and tested a recursive airspeed and thrust estimation (RATE) algorithm. Finally, a simple implementation using Extended Kalman Filter (EKF) is tested and results are compared. The possibility to use angle-of-attack and/or temperature probes is also discussed. We also discuss practical aspects regarding airspeed, altitude and temperature estimations.

Keywords: Air Data System, Synthetic, Kalman

1. Introduction

Airspeed sensors failures and erroneous indications have been issues of concern from certification authorities. As air data probes are sensors exposed to the airflow, they are sensitive to atmospheric conditions such as rain, icing, moisture, volcanic ash and dust. In order to improve air data systems reliability, synthetic air data systems has been under study during last decades.

Synthetic Air Data Systems are essentially airspeed estimation algorithms. Such algorithms are built using measurements from sensors other than the classical Pitot tubes, from which airspeed estimates can be computed. Some works have presented the possibility of determining airspeed based on other systems such as GPS and IRS ([1], [6], [7], [8] and [9]). This paper investigates simple estimation methods presented by [1] and [6], which are applied to the F-16 model from [5] and [2].

The method used is based on C_L estimation, which is computed from the load factor normal to flight path, mass, CG position and initial estimates from angle of attack and airspeed. Basic aircraft model is also assumed as it uses longitudinal moment and lift coefficient curves, matrix of inertia Iy and geometrical parameters.

Some airspeed estimation methods ([7], [8] and [9]) require disturbances to be applied in control inputs, such as doublet signals on the control column or wheels. This study analyzes the method proposed by [1] and [6] and shows that such methods do not require those disturbances on the control inputs. The method is applied to the F-16 model from [5] and discussed some assumptions made by both [1] and [6], proposing a different strategies such as a recursive airspeed and thrust estimation (RATE) and a simple model-based estimation using linear discrete Kalman Filter.

Synthetic airspeed methods may be classified as direct or recursive or dynamic estimation methods as detailed on the following sections.

2. Direct Estimation Methods

2.1 CL estimation based on Y-axis moments: Zeis' Method

According to [1], lift coefficient may be directly estimated based on the balance of (Y-axis) moments generated by lift forces acting on wing-body, horizontal tail, and the moment generated by weight. A simple diagram is presented below on Figure 1.

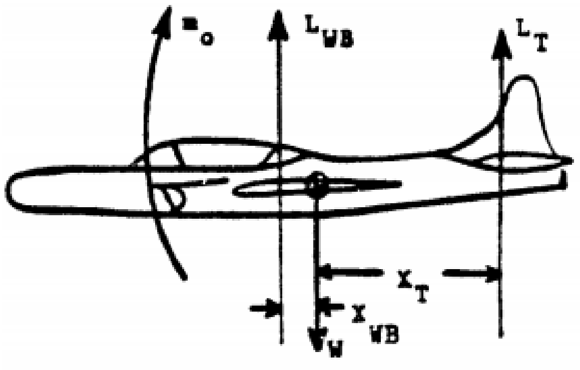

Figure 1 – Forces and moments acting on an aircraft

$$n_Z W = 0.5\rho V^2 S C_{L_{WB}} + L_T \tag{1}$$

The moment equation over the Y axis on body frame can be combined with (1), leading to (2). Reorganizing (2) we get to the equation proposed by Zeis (3).

$$\sum m = m_0 - L_T x_T + L_{WB} x_{WB} = \dot{q} I_y + pr(I_X - I_Z) + (p^2 - r^2) I_{XZ} \tag{2}$$

$$C_{L_{WB}} = \frac{g n_{Z_W} m x_T + \dot{q} I_y + pr(I_X - I_Z) - C_{m_0} 0.5\rho V^2 S\bar{c}}{0.5\rho V^2 S x_T \left[1 + (x_{WB}/x_T)\right]} \tag{3}$$

The angle of attack update is then computed using the lift equation inverse curve $\alpha = f(C_{L_{WB}})$, which will be used as the angle of attack for the lift coefficient estimate on next time step.
The original method is based on accelerometer and inertial systems in order to obtain the acceleration normal to the flight path (see equations below).

$$\mathscr{M}_E^B = \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos\phi & sin\phi \\ 0 & -sin\phi & cos\phi \end{bmatrix} \begin{bmatrix} cos\theta & 0 & -sin\theta \\ 0 & 1 & 0 \\ sin\theta & 0 & cos\theta \end{bmatrix} \begin{bmatrix} cos\psi & sin\psi & 0 \\ -sin\psi & cos\phi & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{4}$$

Considering that side slip angle positive sense is inverse as the positive sense from yaw angle,

$$\mathscr{M}_W^B = \begin{bmatrix} cos\alpha & 0 & -sin\alpha \\ 0 & 1 & 0 \\ sin\alpha & 0 & cos\alpha \end{bmatrix} \begin{bmatrix} cos\beta & -sin\beta & 0 \\ sin\beta & cos\beta & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{5}$$

$$\mathscr{M}_{W_{\beta=0}}^B = \begin{bmatrix} cos\alpha & 0 & -sin\alpha \\ 0 & 1 & 0 \\ sin\alpha & 0 & cos\alpha \end{bmatrix} \tag{6}$$

The acceleration on the wind axis is then $a_W = \mathscr{M}_{B_{\beta=0}}^W a_B$, and thus, the acceleration normal to flight path can be obtained by using (7).

$$a_{z_W} = -a_{x_B} sin\alpha + a_{z_B} cos\alpha \tag{7}$$

Using Euler angles and aerodynamic angles we may compute the gravity acceleration component normal to flight path using (8).

$$g_W = \mathscr{M}_{B_{\beta=0}}^W \mathscr{M}_E^B = \begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix}_E \tag{8}$$

$$g_{W_{\phi=\psi=\beta=0}} = \begin{bmatrix} -g sin\theta cos\alpha \\ 0 \\ g sin(\theta - \alpha) \end{bmatrix} \tag{9}$$

In order to use only the inertial reference system, [1] proposed to assume $\mathscr{M}_B^W = I$, what is equivalent to (10).

$$g_{W_{\phi=\psi=\beta=0}} \approx \mathscr{M}_E^B \begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix}_E \Rightarrow g_{W_{\phi=\psi=\beta=0}} \approx \begin{bmatrix} -g sin\theta \\ g cos\theta sin\phi \\ g cos\theta cos\phi \end{bmatrix} \tag{10}$$

In fact, we can notice that for straight leveled flights (cruise condition), where we may assume $\gamma = \phi = 0$, both the approximation proposed by [1] and the exact formulation above (9) are equivalent.
Finally, we may write the load factor n_{z_W} in terms of forces components on the z_W axis normal to flight path (11).

$$n_{z_W} = \frac{W cos\gamma - m a_{z_W}}{W} \tag{11}$$

$$n_{z_W} = \frac{a_{x_B} sin\alpha - a_{z_B} cos\alpha}{g} + cos(\theta - \alpha) \tag{12}$$

Applying (7) in (11) we get (12). The complete angle of attack estimation workflow is detailed in figure 2.

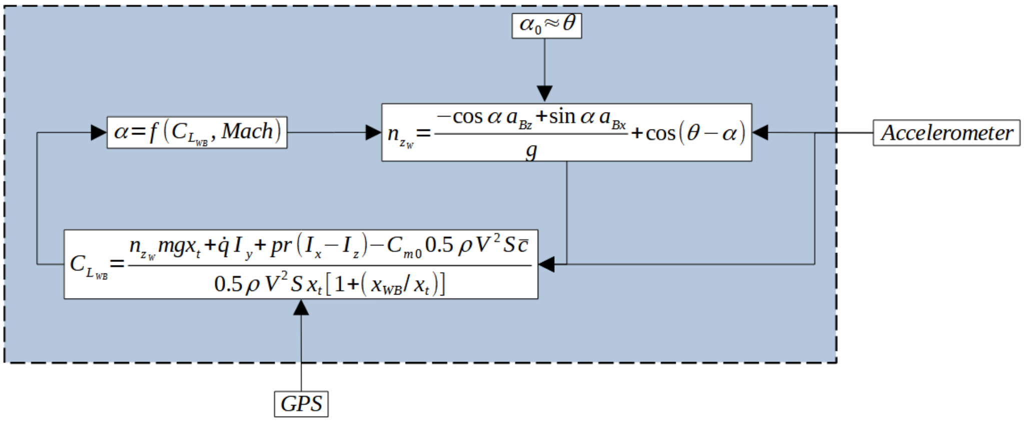

Figure 2 – AOA estimation workflow using Zeis' method

2.2 AOA estimation based on Z-axis forces: Myschik's method

In reference [6] Myschik proposed a simple equation derived from the balance of aerodynamic forces components on Z-axis of wind frame taking into account inertial measurements, aerodynamic derivatives and control surface deflections. We will derive a similar equation, assuming that thrust force is known.
Let us write the equation for balance of forces on Z-axis of wind frame (13).

$$g cos\gamma - \frac{L - T sin\alpha}{m} = a_{Z_W} \tag{13}$$

From (7) we may write (13) in terms of θ, α, C_L and body accelerations as below.

$$C_L \frac{\bar{q}S}{m} = (a_{X_B} sin\alpha - a_{Z_B} cos\alpha) + g cos(\theta - \alpha) - \frac{T sin\alpha}{m} \tag{14}$$

Assuming a linear C_L model accounting for angle of attack, pitch rate and elevator deflection, we may write (15).

$$C_L = C_{L_0} + C_{L_\alpha}\alpha + C_{L_q} q \left(\frac{\bar{c}}{2V}\right) + C_{L_{\delta_e}} \delta_e \tag{15}$$

Combining both equations (15) and (14) we then come to (16).

$$\left[C_{L_0}+C_{L_\alpha}\alpha+C_{L_q}q\left(\frac{\bar{c}}{2V}\right)+C_{L_{\delta_e}}\delta_e\right]\left(\frac{\bar{q}S}{m}\right)=sin\alpha(gsin\theta+a_{X_B}-\frac{T}{m})+cos\alpha(gcos\theta-a_{Z_B}) \tag{16}$$

Using the approximation for small angles ($\alpha \approx sin\alpha$), we may write Myschik's angle of attack estimator with thrust correction effect (17).

$$\alpha \approx \frac{-\left[C_{L_0}+C_{L_q}q\left(\frac{\bar{c}}{2V}\right)+C_{L_{\delta_e}}\delta_e\right]\left(\frac{\bar{q}S}{m}\right)-(a_{Z_B}-gcos\theta)}{\left(\frac{C_{L\alpha}\bar{q}S+T}{m}\right)-(a_{X_B}+gsin\theta)} \tag{17}$$

A workflow for AOA estimation using Myschik's method is presented on Figure 3.

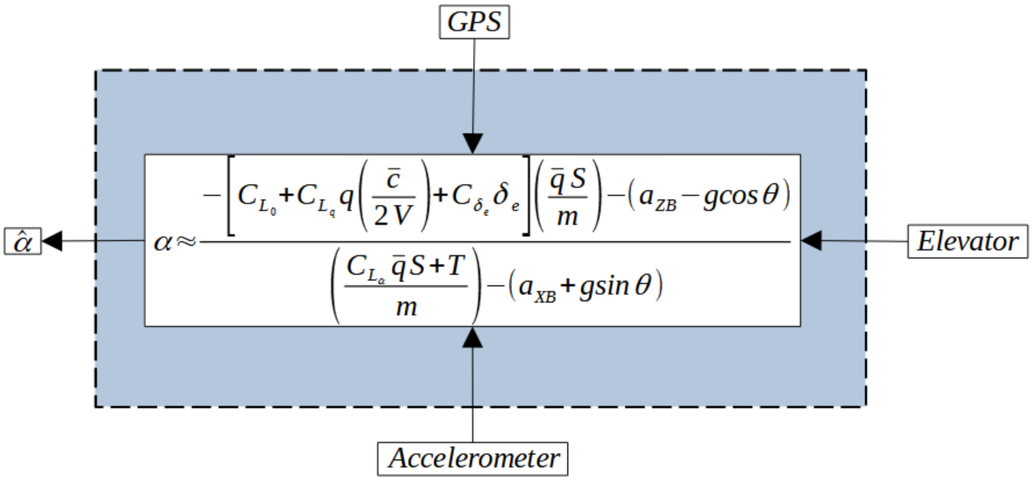

Figure 3 – AOA estimation workflow using Myschik's method

Note: original Myschik's equation did not account for thrust force and did not make gravity acceleration components explicit to compensate body inertial acceleration measurements.

3. Recursive Airspeed and Thrust Estimation (RATE)

Translational kinematics equations can be written in terms of measured body accelerations (18, 19 and 20).

$$\dot{u}=rv-qw-gsin\theta+a_{x_B} \tag{18}$$

$$\dot{v}=pw-ru+gcos\theta sin\phi+a_{y_B} \tag{19}$$

$$\dot{w}=qu-pv+gcos\theta cos\phi+a_{z_B} \tag{20}$$

The body accelerations on the three body axes are defined (21), 22 and 23).

$$a_{x_B}=\frac{\bar{q}SC_X+T}{m} \tag{21}$$

$$a_{y_B}=\frac{\bar{q}SC_Y}{m} \tag{22}$$

$$a_{z_B}=\frac{\bar{q}SC_Z}{m} \tag{23}$$

Equation (21) we can be written in a different form as in (24). Using the dynamic pressure definition ($\bar{q}=0.5\rho V^2$), we find out that airspeed can be estimated using (25)

$$\bar{q}=\frac{ma_{x_B}-T}{SC_X} \tag{24}$$

$$V = \sqrt{\frac{2(ma_{x_B} - T(Mach, Hp, T_P))}{\rho S C_X(\alpha, \delta_e)}} \tag{25}$$

In fact, the aircraft model from [5] and [2] considers thrust as a function of Mach, altitude and thrust power (T_P), where power T_P is determined by the engine transient dynamics and thrust lever position. Thrust can then be modeled by (26). On the other hand, C_X is modeled as a function of AOA and elevator position ($C_X = f(\alpha, \delta_e)$).

$$T = f(Mach, Hp, T_P) \tag{26}$$

If we assume that International Standard Atmosphere (ISA) model represents the atmosphere ([10]), then altitude can be measured by a GPS sensor and temperature is function of altitude. Thus, we may estimate airspeed based on a Mach number guess, altitude and thrust lever position. C_X can be estimated from measurements of elevator deflection and AOA. If we consider that AOA sensor is failed or not installed, we may still use one AOA estimate based on method presented on previous sections (2.1 or 2.2). The estimation workflow is summarized on figure 4.

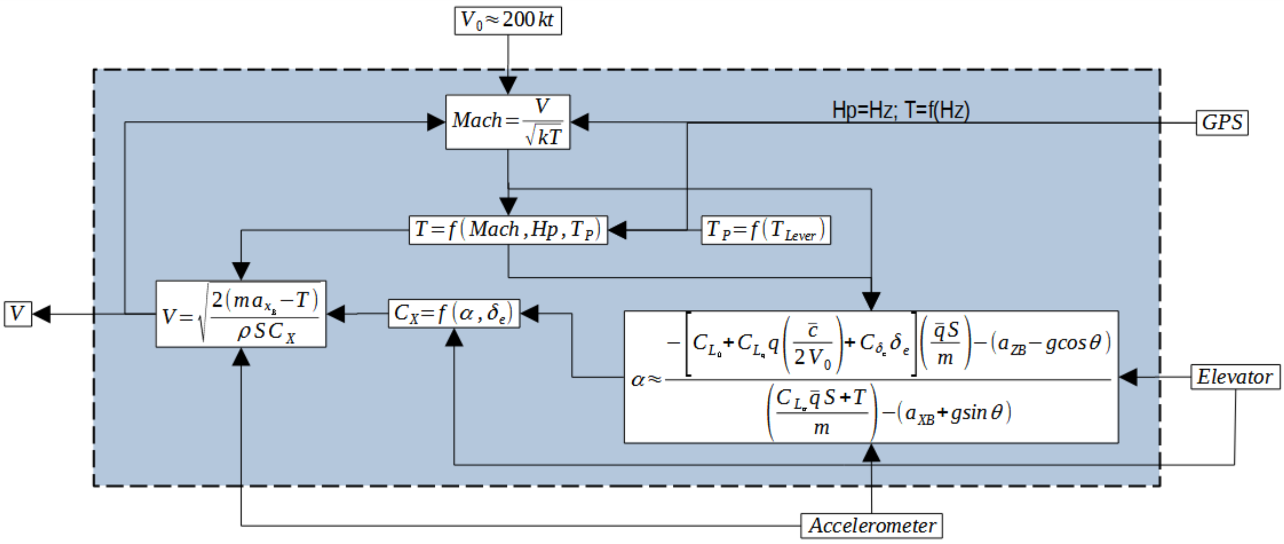

Figure 4 – Recursive Airspeed and Thrust Estimation (RATE) method workflow

4. Dynamic Estimation

The airspeed on the wind axis can be described by (27) as a function of drag (28), thrust (T), mass (m), Euler angles and aerodynamic angles α and β.

$$\dot{V}_g = -\frac{\bar{q}SC_{D_W}}{m} + \frac{T}{m}cos\alpha cos\beta + g(cos\phi cos\theta sin\alpha cos\beta + sin\phi cos\theta sin\beta - sin\theta cos\alpha cos\beta) \tag{27}$$

$$C_{D_W} = -C_X cos\alpha cos\beta - C_Y sin\beta - C_Z sin\alpha cos\beta \tag{28}$$

Let us now define the measured longitudinal acceleration a_W on X-axis in the wind frame by (29).

$$a_W = -\frac{\bar{q}SC_{D_W}}{m} + \frac{T}{m}cos\alpha cos\beta \tag{29}$$

Using (28), we can substitute force coefficients from equations (21), (22) and (23), what leads to (30).

$$a_W = a_{x_B} cos\alpha cos\beta + a_{y_B} sin\beta + a_{z_B} sin\alpha cos\beta \tag{30}$$

Applying (30) in (27) we get (31).

$$\dot{V}_g = a_{x_B} cos\alpha cos\beta + a_{y_B} sin\beta + a_{z_B} sin\alpha cos\beta + g(cos\phi cos\theta sin\alpha cos\beta + sin\phi cos\theta sin\beta - sin\theta cos\alpha cos\beta) \tag{31}$$

Using the equation of the acceleration on the wind frame, and considering accelerations on body frame, it is possible to write speed variation as a function of measured accelerations on body frame, gravity, attitude and aerodynamic angles. This simple equation (31) can represent cruise - a large portion of a flight of a commercial airplane – and leveled accelerations.
Aispeed can be estimated by (25). Since this requires an angle of attack estimate, the angle of attack is initially assumed equal to pitch attitude and is updated each time step using equation (17). It does not require any input of dynamic pressure neither airspeed. In fact, the airspeed is an output of the iterative method depicted in Figure 4 using equation (25).

4.1 Extended Kalman Filter (EKF) model

Extended Kalman filtering is an extension of the well known Kalman Filter. As described on several references ([2], [3] and [4]), Kalman filtering is a statistical filtering technique that composed by two steps:

- Prediction: State prediction on the next time step ($\hat{x}(k|k-1)$). This is done using the system input and actual state estimate ($\hat{x}(k-1|k-1)$) as inputs to the dynamic model (37).
- Update: State updated is a refinement of the predicted state based on the differences from measured outputs (y) and output estimates (40) computed from system model and predicted state ($\hat{y}(k+1|k) = C\hat{x}(k+1|k)$).

A simple dynamic model is assumed here to provide state predictions using Kalman filtering. This model is presented below in equation (32). It assumes a two-state system with ground speed and wind speed state vector ($x = [V_g, V_w]^T$).

$$x_{k+1} = x_k + \begin{bmatrix} \dot{V}_g \Delta t \\ 0 \end{bmatrix} + \zeta \tag{32}$$

We assumed that ground speed can be measured using GPS antennas and that wind speed can also be measured by using the airspeed recursive estimation (RATE) as presented on section 3 and depicted in Figure 4. Thus, it is reasonable to assume that both ground and wind can be measured (33).

$$z = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} x + \nu \tag{33}$$

Process noise matrix is equal to Q (34). It was assumed a very small modeling error for state x_1 and a higher error for state x_2 to allow for non-modeled stochastic wind disturbances.

$$Q = E\left\{\zeta^T \zeta\right\} = \begin{bmatrix} 0.01 & 0 \\ 0 & 0.1 \end{bmatrix} \tag{34}$$

Measurement noise covariance is equal to R (35). As state x_1 is the speed measured from GPS, it was assumed a very small error whem compared against x_2, which is an estimated state (wind speed).

$$R = E\left\{\nu^T \nu\right\} = \begin{bmatrix} 0.01 & 0 \\ 0 & 10 \end{bmatrix} \tag{35}$$

Initial state covariance matrix P_0 is given by (36). Since ground speed can be easily obtained from GPS sensor, $\hat{x}_1$ initial error was assumed relatively small when compared against $\hat{x}_2$, that will be dependent basically on wind estimates and a weak model, as $E\left\{\zeta_2^T \zeta_2\right\} = 10E\left\{\zeta_1^T \zeta_1\right\}$.

$$P_0 = E\left\{\hat{x}_0^T \hat{x}_0\right\} = \begin{bmatrix} 1 & 0 \\ 0 & 999 \end{bmatrix} \tag{36}$$

Since EKF (extended Kalman filter) is a non-linear generalization of the Kalman filter, it requires the same two steps (prediction and update) as the original Kalman filter. Prediction step uses equations

(37), (38) and (39); update step uses equations (40), (41) and (42). Specifically for the EKF, it is required that some linearizations are provided (43) and (44).

Prediction step:

$$\hat{x}(k|k-1) = \Phi(k-1)\hat{x}(k-1|k-1) + \nu(k-1) \tag{37}$$

$$\hat{y}(k|k-1) = h(\hat{x}(k|k-1), u(k)) \tag{38}$$

$$P(k|k-1) = \Phi(k-1)P(k-1|k-1)\Phi^T(k-1) + \Gamma(k-1)Q(k-1)\Gamma^T(k-1) \tag{39}$$

Update step:

$$\hat{x}(k|k) = \hat{x}(k|k-1) + K(k)[z(k) - \hat{y}(k|k-1)] \tag{40}$$

$$K(k) = P(k|k-1)C^T(k)[C(k)P(k|k-1)C^T(k) + R(k)]^{-1} \tag{41}$$

$$P(k|k) = [I - K(k)C(k)]P(k|k-1) \tag{42}$$

Linearized functions Φ and C:

$$\Phi(k-1) = \frac{\partial f[x, u(k-1)]}{\partial x}|_{x=\hat{x}(k-1|k-1)} \tag{43}$$

$$C(k) = \frac{\partial h[x, u(k)]}{\partial x}|_{x=\hat{x}(k|k-1)} \tag{44}$$

5. Simulation Results

This section presents the simulation results for the methods presented on sections 2 and 3. Simulations have been performed assuming a straight leveled flight, with parameter values as presented on Table 1.

Table 1 – Parameters used in simulations

Parameter	Value	Unit
σ_η	2.5	ft/s
T_s	0.1	s
Airspeed	500	ft/s
Altitude	36,000	ft
CG	20	% mac
Wind Speed North	50	kt
Wind Speed East	0	kt

5.1 Wind Model

Wind speed is commonly modeled ([7] and [9]) as a first order Gauss-Markov process. We opted to use a simplified model in discrete time basis (45), with $\sigma_\eta^2 = E\{\eta^T\eta\}$.

$$V_{w_{k+1}} = V_{w_k} + T_s\eta \tag{45}$$

The airspeed can be computed in terms of wind an ground speeds by the relation $V_t = V_g + V_w$. We can also write wind speed using the Earth reference system, what leads to (46). Note that vertical wind is assumed equal to zero.

$$V_t = V_g + \mathscr{M}_E^B \begin{bmatrix} VwN \\ VwE \\ 0 \end{bmatrix} \tag{46}$$

According to [5], the derivative of a rotation matrix (i.e. $\mathscr{M}_E^B$) is the cross-product of angular speed vector times the rotation matrix. If we express the vector cross product as the product of a skew-symmetric matrix we get (47). If we derive (46) using the chain rule and use (47), we find (48).

$$\dot{\mathscr{M}}_E^B = -\begin{bmatrix} 0 & -r & q \\ r & 0 & -p \\ -q & p & 0 \end{bmatrix} \mathscr{M}_E^B \tag{47}$$

$$\dot{V}_t^B = \dot{V}_g^B + \mathscr{M}_E^B \dot{V}_w - \begin{bmatrix} 0 & -r & q \\ r & 0 & -p \\ -q & p & 0 \end{bmatrix} \mathscr{M}_E^B V_w \tag{48}$$

5.2 AOA and CL estimations

Figure 5 presents a comparison of the direct estimation methods detailed on section 2. Angle of attack is used to determine lift coefficient C_L to compute airspeed estimate according to (49).

$$V = \sqrt{\frac{2W}{\rho S C_L(\alpha)}} \tag{49}$$

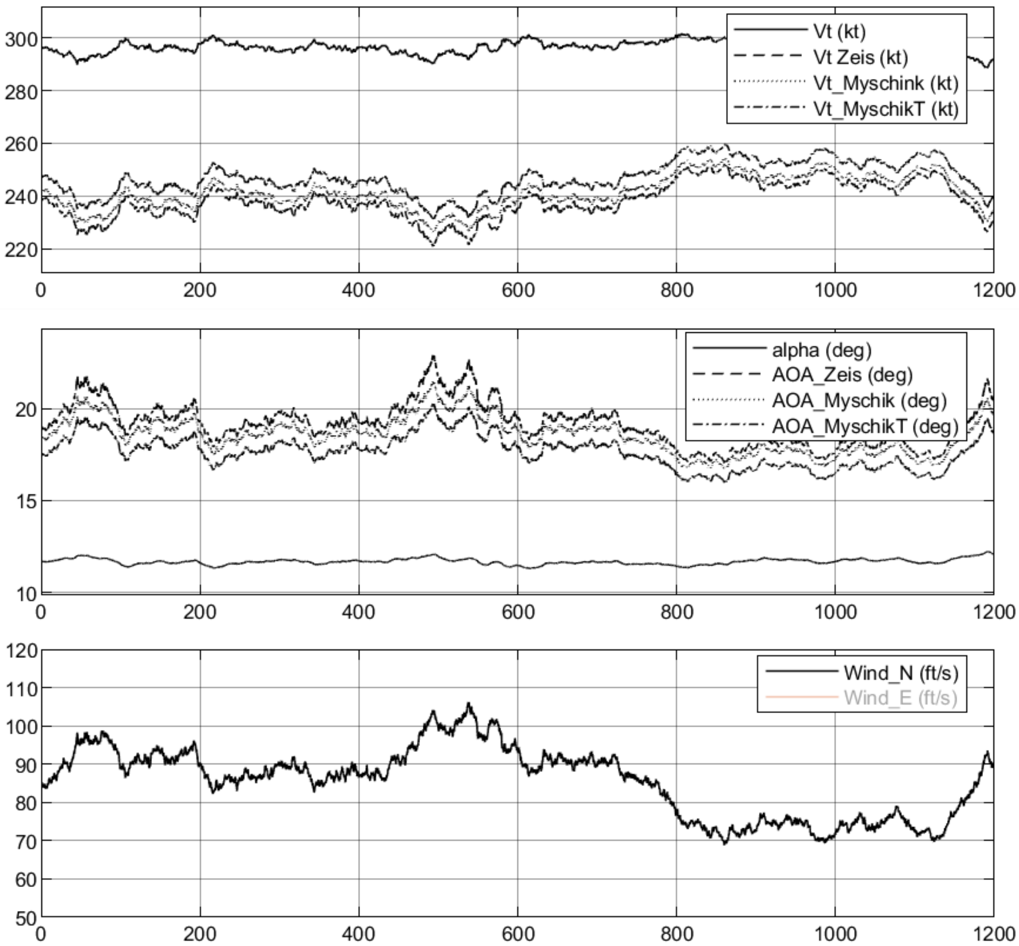

Figure 5 – Airspeed and AOA estimates comparison

If we take a close look in figure 5 we can see some aspects related to the estimates for all the methods:

- All the three methods provide consistent estimates, with similar errors when compared against real values of AOA and airspeed;
- There is a correlation between wind speed and the direct estimates. This is occurs because all the methods require a value of dynamic pressure as input (see equations (3) and (17)). Ground speed from GPS was used as input for those estimations.

5.3 Recursive Airspeed and Thrust Estimation (RATE)

Figure 6 presents the results of RATE method applied to simulation data. The angle of attack estimate is initially assumed equal to pitch attitude and is updated each time step using Myschik's equation (17). It does not require any input of dynamic pressure neither airspeed. In fact, the airspeed is an output of the iterative method depicted in Figure 4 using equation (25).

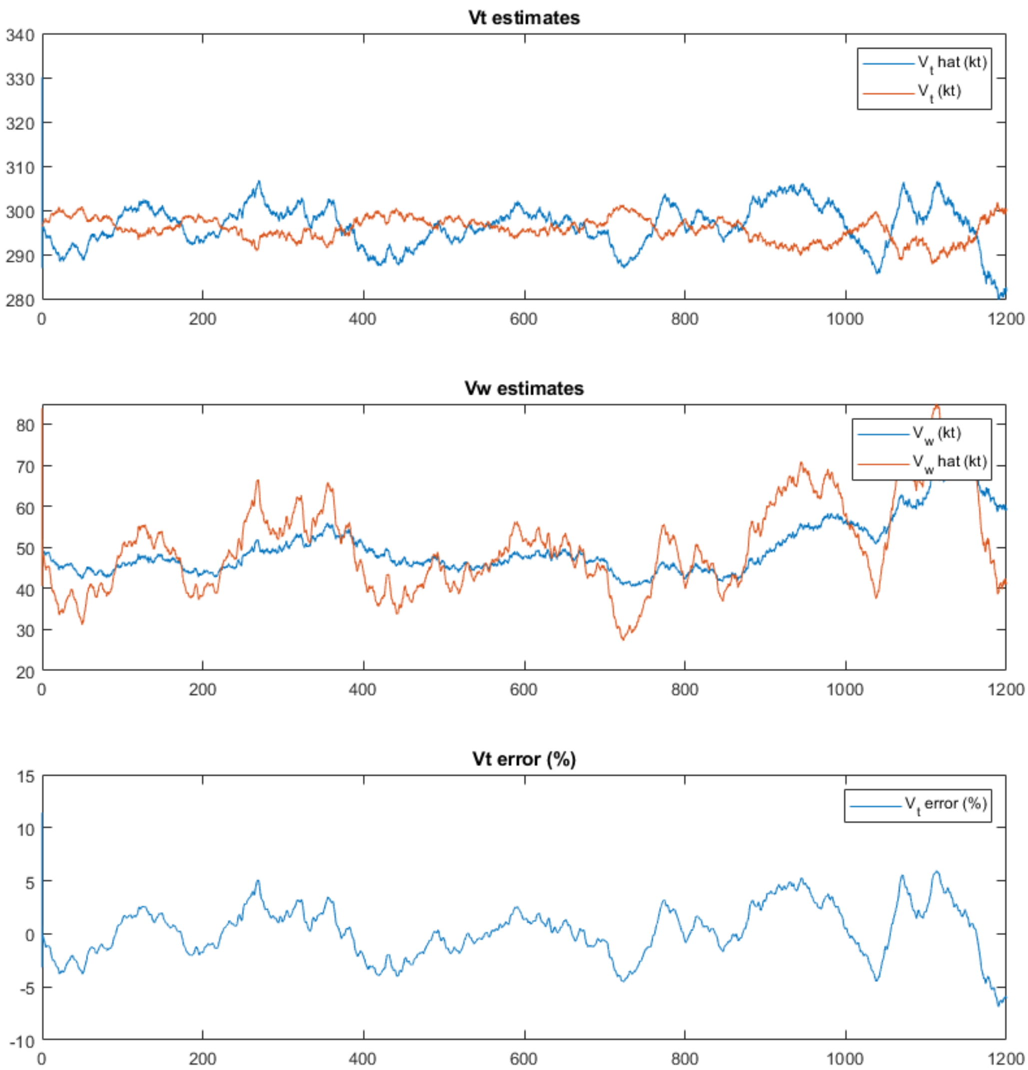

Figure 6 – RATE estimation results

5.4 Dynamic Estimation

Results from the Kalman filtering estimation (sec. 4) are presented in Figure 7, while a comparison between the RATE method (sec. 3) and Kalman filtering is presented in Figure 8.

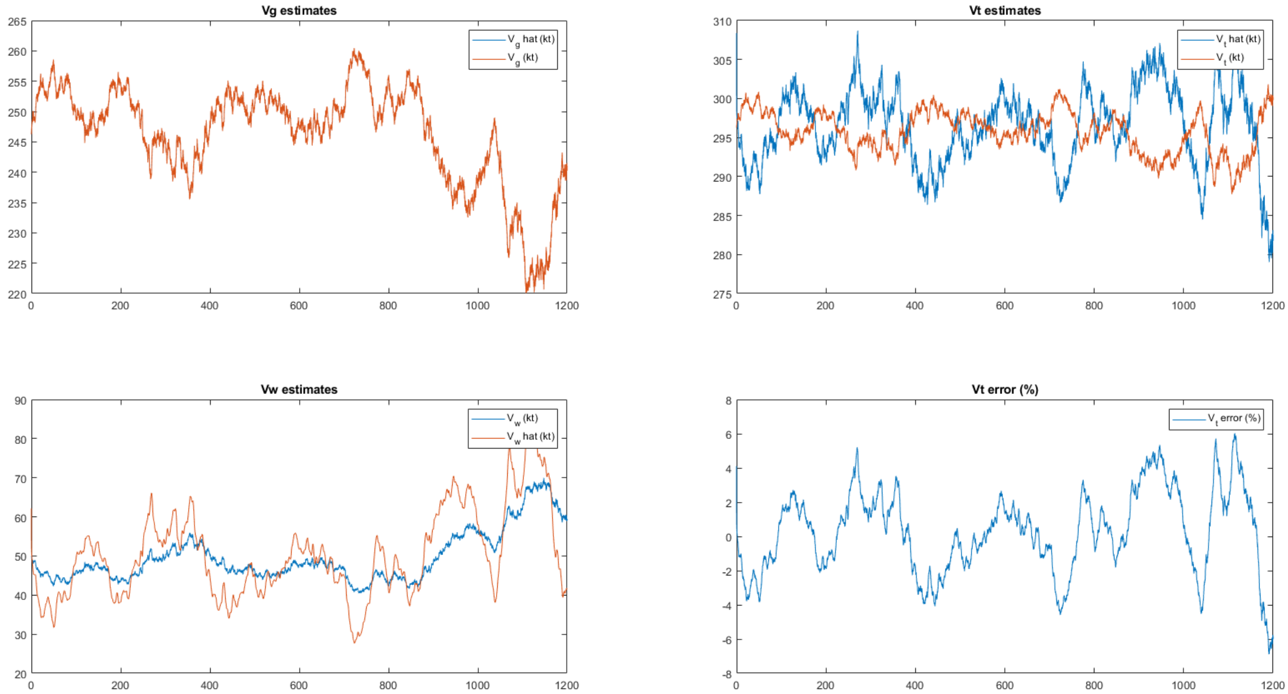

Figure 7 – EKF estimation results

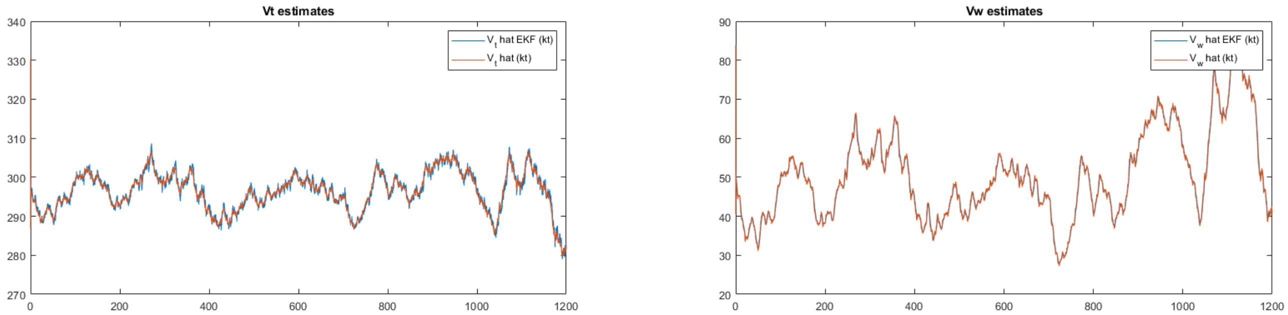

Figure 8 – EKF vs. Recursive Estimation (RATE) results comparison

6. Conclusions

The F-16 dynamic model could be modified to incorporate wind dynamics, that have been modeled by a first-order Gauss-Markov process. The following direct estimation methods have been compared, presenting similar results:

- Zeis: method proposed in [1] that uses angular moments on Y axis
- Myschik: method proposed in [6] that uses forces on vertical wind axis
- MyschikT: modified version of Myschik's method that incorporates thrust information (17).

A recursive airspeed and thrust estimation (RATE) method, that uses acceleration on X wind axis was proposed. As this method requires angle of attack as input, an AOA estimate based on one of the methods presented on section 2 may be used. Alternativaly, if it can be assumed that a given air data system has a reliable AOA sensor, direct measurements may also be used with more accurate results.

In fact, the results presented on section 5.3 used Myschik's equation for AOA estimates. This approach presented results not dependent on wind speed since AOA estimates are based on a time-varying airspeed estimate (figure 4), differently from pure Myschik's method (figure 3), that had to use ground speed (from GPS) as first airspeed estimate. Such assumption is equivalent to zero wind assumption.

Finally, an implementation of Extended Kalman filter with a two-state internal model has been compared against RATE method. Both showed similar results.

7. Acknowledgement

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8. Copyright Statement

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