Flight Control Research Laboratory Unmanned Aerial System flying in turbulent air: an algorithm for parameter identification from flight data

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This work addresses the identification of the dynamics of the research aircraft FCRL (Flight Control Research Laboratory) used for the Italian National Research Project PRIN2008 accounting for atmospheric turbulence.

The subject vehicle is an unpressurized 2 seats, 427 kg maximum take of weight aircraft. It features a non retractable, tailwheel, landing gear and a powerplant made up of reciprocating engine capable of developing 60 HP, with a 60 inches diameter, two bladed, fixed pitch., tractor propeller. The aircraft stall speed is 41.6 kts, therefore it is capable of speeds up to about 115 kts (Sea level) and it will be cleared for altitudes up to 10.000 ft. The studied aircraft is equipped with a research avionic system composed by sensors and computers and their relative power supply subsystem. In particular the Sensors subsystem consists of :

- Inertial Measurement Unit (three axis accelerometers and gyros)
- Magnetometer (three axis)
- Air Data Boom (static and total pressure port, vane sense for angle of attack and sideslip)
- GPS Receiver and Antenna
- Linear Potentiometers (Aileron, Elevator, Rudder and Throttle Command)
- RPM (Hall Effect Gear Tooth Sensor)
- Outside air temperature Sensor

A nonlinear mathematical model of the subject aircraft longitudinal dynamics, has been tuned up through semi empirical methods, numerical simulations and ground tests.

To taking into account the atmospheric turbulence the identification problem addressed in this work is solved by using the Filter error method approach .In this case, the mathematical model is given by the stochastic equations:

$$
\begin{aligned}
\dot{x}(t) &= f\left(x(t), u(t), w(t), \theta\right) \\
y(t) &= h\left(x(t), u(t), \theta\right) \\
z(k) &= y(k) + v(k) \\
x(t_0) &= x_0
\end{aligned}
\tag{1}
$$

where x is the state vector, u is the control input vector, f and h are dimensional general nonlinear vector functions, θ contains the unknown system parameters, z is the measurement vector ,w is the process noise and $v(k)$ is the measurement noise. The presence of nonmeasurable process noise requires a suitable state estimator to propagate the states. To take into account model nonlinearities in the present paper an Extended Kalman Filter has been implemented as the estimation algorithm.