Online Near Real-Time System Identification of a Small Unmanned Aircraft System

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Abstract

We developed an Online Near Real-Time System Identification method using Observer/Kalman Filter Identification as a candidate for identifying localized linear rigid body aircraft dynamics. High frequency data updates are required for online identification. This research presents a custom flight test instrumentation system that is capable of providing accurate full-state and control deflection measurements and develop a system that is capable of conducting system identification at a near real time fashion with human-in-the-loop update procedures for Small Unmanned Air Systems.

Motivation

- Common open-source flight controllers have the ability to log state data, but they often are unable to log at the required rates to obtain good identification of model characteristics, and often are unable to log important flow parameters such as angle-of-attack and sideslip angle.
- The process of acquiring linear models for different UAS is tedious and require a lot of post processing and experience.
- Current existing online system identification algorithms require state estimation and aircraft specific measurements for SUAS.
- There is a need for reliable automated excitation for system identification.
- To provide model updates in the air and use the updated model to perform controller design.

Technical Approach

The proposed online near real-time system identification procedure is shown in Figure 1. To perform reliable excitation for online applications, an automated excitation is implemented. The system can be split into three subsystems: the data acquisition subsystem, the system identification subsystem, and the control design subsystem. The system identification subsystem performs an recursive Observer Kalman Filter Identification (OKID) to acquire the local linear model. OKID calculates a least square solution for the data set and returns the observer gain along with system matrices that can be used for controller design.

$$\dot{\hat{x}} = A_l\hat{x} + B_l u$$
$$\hat{y} = C_l\hat{x} + D_l u$$

Quality indexes including Weighted Modal Phase Collinearity (MPCW), Extended Modal Amplitude Coherence (EMAC), Modal Singular Value (MSV), and Consistent Mode Indicator (MCI) are calculated to separate structural modes from noise modes for each updated identification. The updated quality index is then compared with both previous and nominal system matrices. The values are sent to the ground control station and shown on a GUI for the ground control operator to make the update decision. The human operator has the authority to regain control authority at all times. Model based Predictive Control (MPC) is expected to perform a controller design according to the updated characteristics using Observer Markov Parameters during flight. The multi-step prediction equation is

$$y_p(\mathrm{k}) = \Gamma \mathrm{u}_p(\mathrm{k}) + \mathrm{Bu}_p(\mathrm{k}-\mathrm{p}) - \mathrm{Ay}_p(\mathrm{k}-\mathrm{p})$$

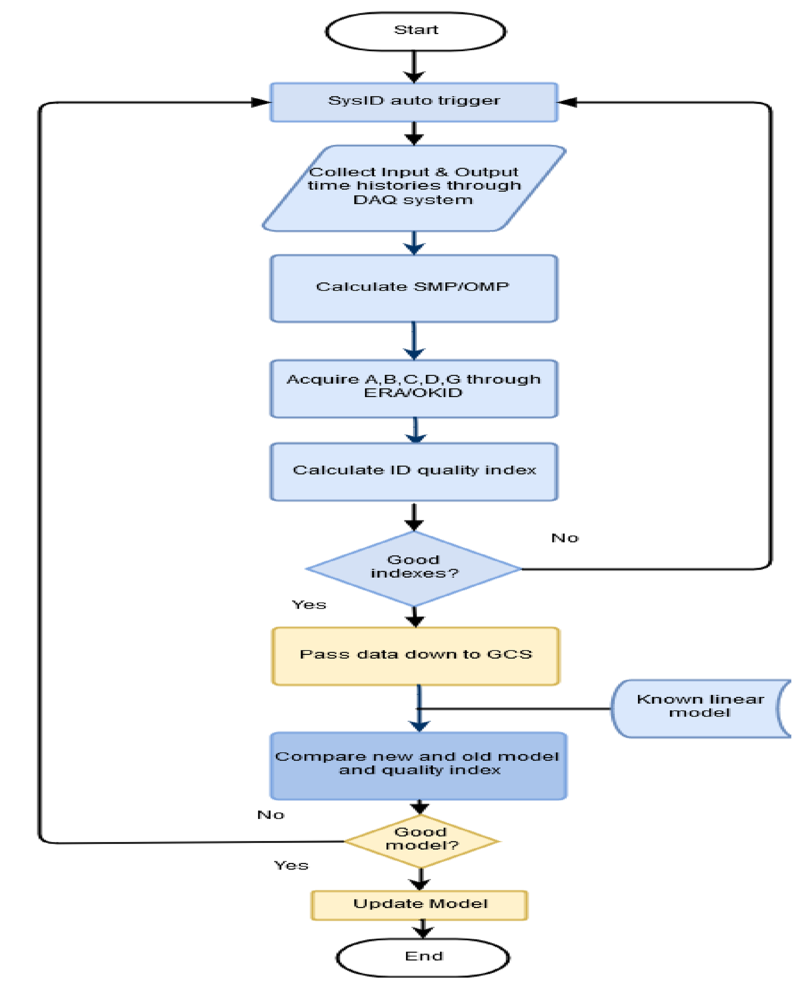

Figure 1. Online system identification flow chart

Defining an error and cost function

$$\varepsilon = y_d(\mathrm{k}) - y_p(\mathrm{k})$$
$$J = \varepsilon^T Q \varepsilon + u_p^T R u_p$$

And minimizing J with respect to $u_p(k)$

$$u_p(k) = -(\Gamma^T Q \Gamma + R)^{\dagger}\Gamma^T Q\left[-y_d(k) + \mathrm{B}u_p(k-p) - \mathrm{A}y_p(k-p)\right]$$

The control input for the future time steps can be calculated.

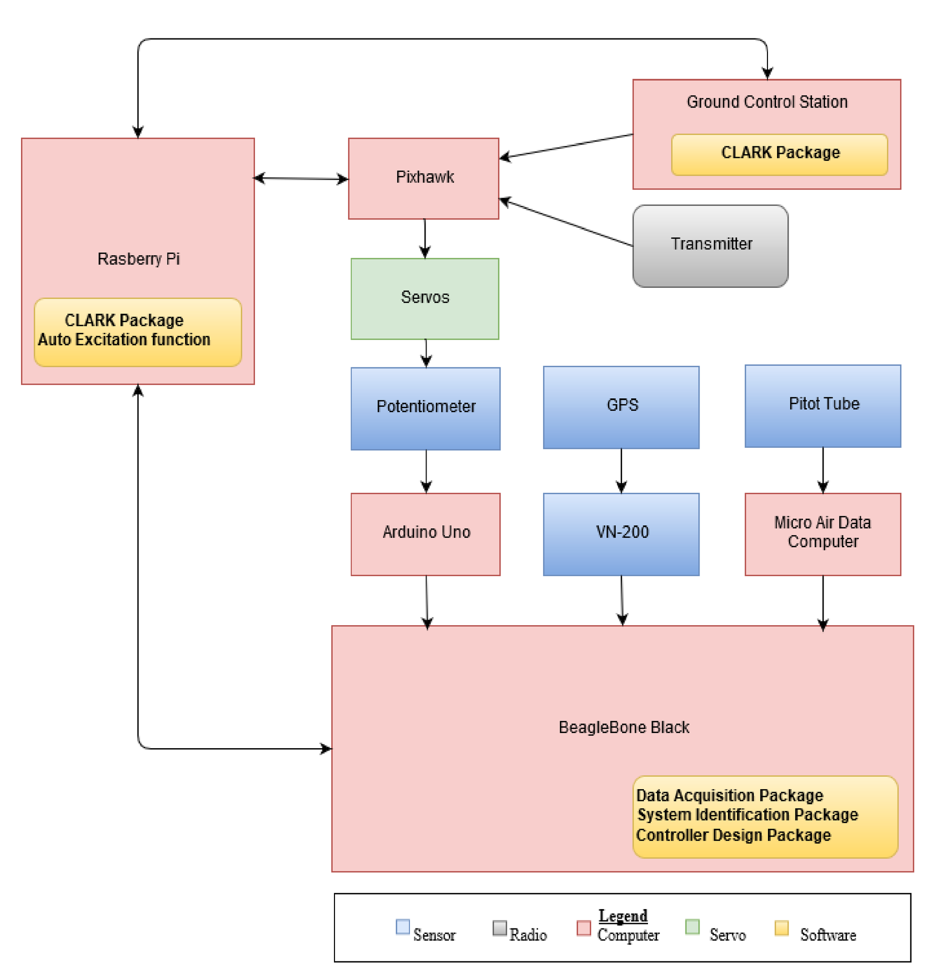

Figure 2. System structure

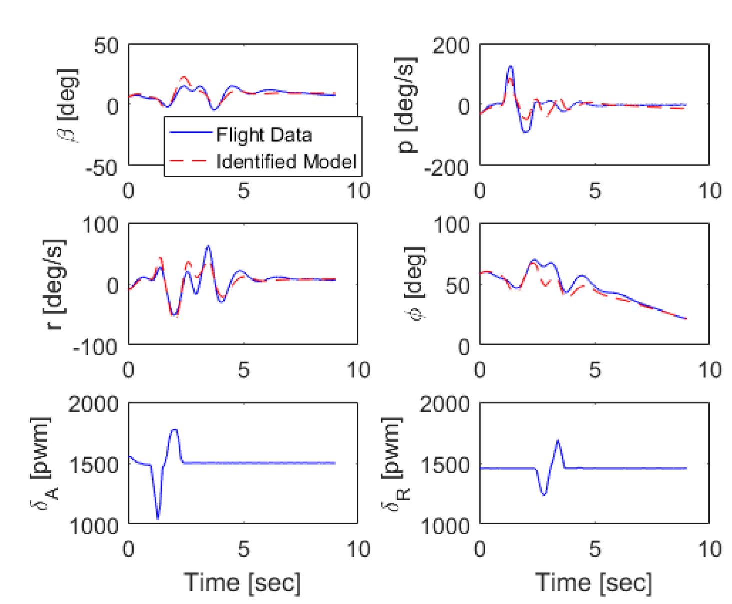

Figure 3. Lat/D identification results.

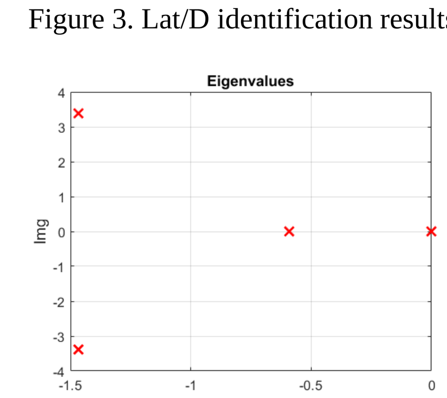

Figure 4. Lat/D modes

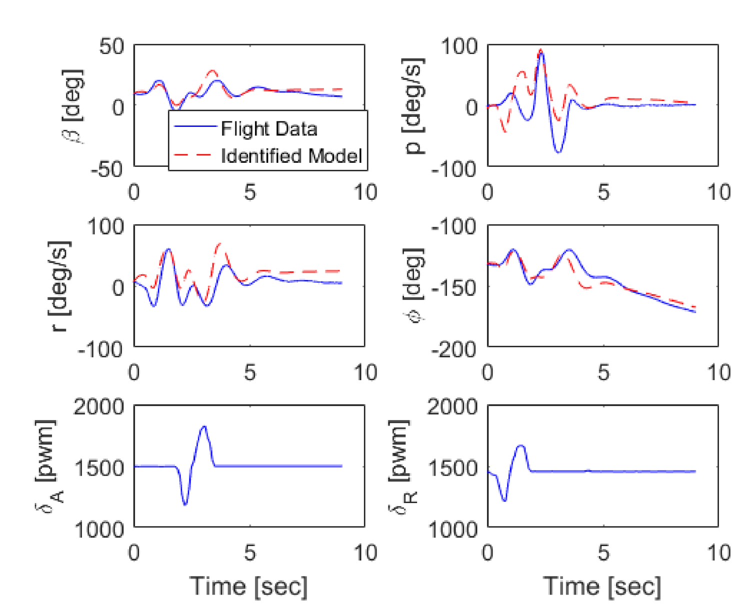

Figure 5.Verification of Lat/D identification results.

$$\begin{Bmatrix}\dot{\beta}\\ \dot{p}\\ \dot{r}\\ \dot{\phi}\end{Bmatrix} = \begin{bmatrix} 0.5016 & 0.0090 & -0.9220 & -0.0978\\ 6.2625 & -1.1999 & -2.1367 & 0.8037\\ 17.9624 & -1.6965 & -2.8225 & 1.2490\\ -0.2651 & -0.1040 & -0.8184 & -0.0047\end{bmatrix}\begin{Bmatrix}\beta\\ p\\ r\\ \phi\end{Bmatrix} + \begin{bmatrix} -0.0005 & 0.0007\\ -0.0102 & 0.0111\\ -0.0137 & 0.0147\\ 0.0001 & 0.0000\end{bmatrix}\begin{Bmatrix}\delta_{\mathrm{A}}\\ \delta_{\mathrm{R}}\end{Bmatrix}.$$

Figure 6. Identified Lat/D system matrix.

The Hangar-9 PA-18 Super Cub is used for flight data collection. The external IMU used is the Vectornav VN-200 supplying attitude angles and angular rates at 100 Hz and GPS information at 5Hz via UART. The Aeroprobe five-hole probe and μADC are installed to collect the velocity u, AOA, and β. Potentiometers are installed on the control surfaces to acquire direct control deflection angles.

Conclusions

A flight test instrumentation system for aircraft state and control time histories to support parameter and system identification is shown. The system features a modular design supporting sensors including air data and inertial navigation systems and can log all required information at 100 Hz. The Observer/Kalman Identification (OKID) algorithm is applied to flight test data obtained using the new flight test instrum-entation package to generate linear state-space models. Results presented demonstrate that the system developed in the paper produces identified rigid-body linear state-space models of fixed wing Unmanned Air Systems that match recorded flight data reasonably well.

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