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Online system identification of mini cropped delta UAVs using flight test methods

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ABSTRACT

The current manuscript presents the longitudinal and lateral directional online parameter estimation of two unmanned aerial vehicles (UAVs) using sequential Least Squares formulation in frequency domain. The two fixed wing UAVs share a similar cropped delta planform and differ in their cross sectional geometries, one with a rectangular and the other being a reflex airfoil cross sections respectively. Recursive Fourier Transform algorithm has been used to convert the flight data in time domain to frequency domain which is measured by means of a dedicated on-board data acquisition system capable of on-board logging and telemetry to ground station. The combination of Sequential Least Squares with Recursive Fourier Transform (SLS-RFT) in frequency domain can be used to carry out online parameter estimation. An attempt has been made to check the applicability of the current method to estimate parameters from the generated flight data of the two UAVs using both conventional as well as random control inputs. Results showed that the parameters estimated, using SLS-RFT, from the linear flight data are consistent and in close agreement with the obtained parameters from full scale wind tunnel testing of UAVs. It was also observed that the estimates from the manoeuvres with multistep control inputs converged faster compared to the parameters obtained from the manoeuvres with slow varying control surface deflections. The time varying linear aerodynamic parametric model of SLS-RFT was able to capture the dynamics of the flights with nonlinear aerodynamics. Certain limitations of the current online system identification method were also observed with estimating parameters from the flight data of UAVs performing near stall manoeuvres. The estimated parameters using SLS-RFT are also compared with the results obtained from batch methods namely classical Maximum Likelihood (ML) and neural based Neural–Gauss–Newton (NGN) methods.

Introduction

In the era of computer automation and smart technology, Unmanned Aerial vehicles (UAVs) became a salient trait of modern defence. Personnel safety, cost effectiveness and ease of operation have made the UAVs to take the driving seat in military to perform "*dull, dirty and dangerous*" jobs [1]. Home land security, surveillance, national defence, disaster response, remote sensing, law enforcement, intelligence and reconnaissance are some of their major applications in military. UAVs also find various applications in civilian as well as business sectors. Although UAVs are widely used for military applications, one issue of the major concern is their performance in fragile atmospheric conditions. Since most of the missions for UAVs demand its flight to be out of sight, the accuracy of the on-board controller plays a major role in successful accomplishment of the mission. The efficiency of modern controllers, that are used to deploy UAVs, directly depends upon the aerodynamic behaviour of the flight vehicle. Moreover, the flight velocities of UAVs are relatively low and the aerodynamics is highly vulnerable to atmospheric disturbances. A robust controller can address these issues by adapting to the changing atmospheric conditions as well as flight regimes [2]. In this case, online system identification can be used as an input to the controller which enables it to adapt for the aforementioned circumstances.

System identification process, for an aircraft, consists of quantifying the unknown aerodynamic parameters that are present in a given aerodynamic model [3]. While using offline/batch estimation methods it is assumed that the aerodynamic model is constant throughout the process, which limits the estimated aerodynamic parameters for a particular flight regime. In contrast, online system identification technique considers a linear aerodynamic model with time varying parameters. The linear aerodynamic model at

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Nomenclature

- a_x, a_y, a_z Accelerations along x-, y- and z-body axes .... m/s^2
- b Span of the aircraft ..... m
- $\bar{c}$ Mean aerodynamic chord ..... m
- C_L, C_D, C_m Longitudinal aerodynamic force and moment coefficients
- C_y, C_l, C_n Lateral directional aerodynamic force and moment coefficients
- $C_{L_0}, C_{D_0}, C_{m_0}$ Longitudinal force and moment coefficients at zero angle of attack
- $C_{y_0}, C_{l_0}, C_{n_0}$ Lateral directional force and moment coefficients at zero sideslip angle
- $C_{L_\alpha}, C_{D_\alpha}, C_{m_\alpha}$ Derivatives of longitudinal force and moment coefficients w.r.t angle of attack
- $C_{y_\beta}, C_{l_\beta}, C_{n_\beta}$ Derivatives of lateral directional force and moment coefficients w.r.t sideslip angle
- $C_{L_q}, C_{D_q}, C_{m_q}$ Derivatives of longitudinal force and moment coefficients w.r.t pith rate
- $C_{y_p}, C_{l_p}, C_{n_p}$ Derivatives of lateral directional force and moment coefficients w.r.t roll rate
- $C_{y_r}, C_{l_r}, C_{n_r}$ Derivatives of lateral directional force and moment coefficients w.r.t yaw rate
- $C_{L_{\delta e}}, C_{D_{\delta e}}, C_{m_{\delta e}}$ Derivatives of longitudinal force and moment coefficients w.r.t elevator deflection
- $C_{y_{\delta a}}, C_{l_{\delta a}}, C_{n_{\delta a}}$ Derivatives of lateral directional force and moment coefficients w.r.t aileron deflection
- $C_{y_{\delta r}}, C_{l_{\delta r}}, C_{n_{\delta r}}$ Derivatives of lateral directional force and moment coefficients w.r.t rudder deflection
- g Acceleration due to gravity ..... m/s^2
- I_x, I_y, I_z Moment of inertia about x, y and z body axis respectively ..... kg m^2
- J Cost function
- m Aircraft mass ..... kg
- p, q, r Roll, pitch and yaw rates respectively ..... rad/s
- S Wing planform area ..... m^2
- u, v, w Airspeed components along x, y and z axis of aircraft respectively ..... m/s
- V Airspeed ..... m/s
- α Angle-of-attack ..... deg
- β Angle of sideslip ..... deg
- $\delta_a, \delta_e, \delta_r$ Aileron, elevator and rudder deflection angles ... deg
- ϕ, θ, ψ Angles of roll, pitch and yaw ..... deg
- ρ Air density ..... kg/m^3
- Θ Vectors of unknown parameters
- ω Frequency of interest ..... rad/s

Subscript

- m Measured quantity

Superscripts

- $\cdot$ Derivative with respect to time
- $\sim$ Flight data in frequency domain
- $\dagger$ Conjugate transpose

each sample time is estimated by using a recursive formulation of ordinary least squares in frequency domain [4]. This recursive nature enables the algorithm to store the information from previous data and avoids reprocessing of old data which makes the procedure efficient for real-time operations. Since this algorithm applies for the frequencies where the system dynamics is involved, the wide band noise is automatically filtered out.

In the recent decade, due to the advancement of micro controller based on-board processors have facilitated greater onboard computational power and also enabled many researchers to advance further in the field of parameter estimation of small and micro UAVs. Suk et al. have used a constrained parameter optimization algorithm to estimate aerodynamic parameters from the flight tests of a conventional fixed wing UAV [5]. Chowdhary and Jategaonkar have compared the performance of Extended Kalman filter (EKF), simplified and augmented versions of Unscented Kalman Filter (UKF) methods in estimating the parameters from the flight data, in time domain, of fixed wing aircraft (HFB-320) and a rotary wing UAV (ARTIS) [6]. Condomines et al. have used UKF to estimate the wind field, subsequently the aerodynamic parameters; of a small scale glider UAV (Solius glider) [7]. Meng et al. have extended the application of iterated EKF to estimate the parameters from the simulated nonlinear flight data of a small fixed wing UAV [8]. Padayachee has used the regression analysis and maximum likelihood method to perform aerodynamic model identification, from flight data, of a twin boom electrically powered fixed wing UAV [9]. Chase and McDonald demonstrated the estimation of longitudinal aerodynamic force coefficients, from the flight tests of fixed wing UAV, using Least Squares and Kalman Filter regression models [10]. Hoffer et al. have used Recursive Least Squares (RLS) algorithm with the error filtering online learning scheme to develop the aerodynamic model of a low-cost-fixed-wing T-tail UAV [11]. Morelli has performed the real time parameter estimation in the frequency domain of F-18 high alpha research aircraft with recursive least square formulation [12]. Morelli has also extended the real time system identification to identify the linear dynamic models of F15 ACTIVE aircraft with multiple control surfaces [13]. Park et al. have used real time system identification to figure out the fault in the control surface of DURUMI-II UAV from flight tests [14]. Ruschmann et al. have carried out the identification of structural damage scenarios of a generic transport model using modified sequential least squares formulation [15]. Jameson and Cooke have used least squares formulation in frequency domain to carry out the online parameter estimation of Jetstream-31 aircraft in the absence of flow angularity sensors [16]. Song et al. have used recursive Fourier transform to perform online parameter identification from NASA F/A-18 Harv flight data [17]. From the aforementioned literature it is observed that the majority of research on system identification of UAVs was carried out using post processing methods. It is also noted that the real time system identification was performed using the flight data, from limited flight regimes, of manned aircraft. In order to use the online system identification as an input for real-time reconfigurable control, the method needs to be verified over various/exhaustive flight envelopes which also include distress conditions. These adverse conditions may include uncontrolled pre and post stall flight, aircraft undergoing icing conditions, control surface failures and sensors malfunctioning etc. to name a few. Generating such flight data using manned aircraft is highly challenging as well as safety concern. Instead of manned aircraft UAVs can be accommodated to overcome the aforementioned limitations.

Unlike the previous works mainly focusing on system identification using post-processing or batch methods for a fixed aerodynamic model, the present research work is aimed at online parameter estimation of a time-varying aerodynamic model from real-time flight data using sequential least squares formulation in frequency domain. For this purpose, two UAVs with cropped delta planform have been designed, fabricated, instrumented and flight

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