Real-Time System Identification of a Small Multi-Engine Aircraft

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In-flight identification of an aircraft's dynamic model can benefit adaptive control schemes by providing estimates of aerodynamic stability derivatives in real time. This information is useful when the dynamic model changes severely in flight such as when faults and failures occur. Moreover a continuously updating model of the aircraft dynamics can be used to monitor the performance of onboard controllers. Flight test data was collected using a sum of sines input implemented in closed loop on a twin engine, fixed wing, Unmanned Aerial Vehicle. This data has been used to estimate a complete six degree of freedom aircraft linear model using the recursive Fourier Transform Regression method in frequency domain. The methods presented in this paper have been successfully validated using computer simulation and real flight data. This paper shows the feasibility of using the frequency domain Fourier Transform Regression method for real time parameter identification.

I. Introduction

Aircraft system identification involves the determination of a dynamic model from in flight measurements. Since the general behavior aircraft dynamic models is known, the problem is becomes one of parameter estimation. If an aircraft can be sufficiently instrumented and all necessary quantities measured, the process can be done in real-time. Many methods of real-time system identification[1,2,3] have been researched. The Fourier Transform Regression (FTR) method is one such method which has been verified to provide accurate results by multiple sources. The FTR method estimates aircraft aerodynamic derivatives by using a recursive least square method in the frequency domain.

In this paper, we present results from recursive system identification for a fixed wing UAV (Unmanned Aerial Vehicle) using the FTR method. The UAV under consideration (GT Twinstar) is fixed wing UAV made from resellient Styrofoam material with a wing span of 4.7 feet maintained by the UAV Research Facility at the Georgia Institute of Technology. GT Twinstar is intended to be a test vehicle for implementation and analysis of fault tolerant control methods and metrics based adaptive control. The purpose of this paper is to develop and validate a linear model for GT Twinstar using the recursive frequency domain FTR method. The system identification methods presented in this paper are conducive to real time implementation. The results from this effort assert the feasibility of implementing the FTR method in real time for online parameter identification.

II. The Georgia Tech Twinstar Unmanned Aerial Vehicle

The Twinstar, produced by Multiplex, is a commercially available multi-engine model-scale aircraft[5]. The Twinstar is made from highly resellient Styrofoam material and is an ideal candidate for fault tolerant control work. This vehicle has been designed such that it will be easy to produce faults in flight

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ranging from control surface failures to actual structural damage and wing breakage. The vehicle has been instrumented with the Adaptive Flight Incorporated (AFI, www.adaptiveflight.com) FCS 20® [6] onboard flight computer system. The FCS 20 is a complete autopilot with a reliable navigation solution which fuses output from multiple embedded sensors to provides high fidelity measurements of aircraft body velocity, angular velocity, Euler angles, and global position. Autopilot software written by Georgia Tech, required for fixed wing navigation has been loaded onto the FCS 20. Further structural modifications have been made to adequately instrument the aircraft for research flights. Data recording capabilities allow for measurement of values needed to perform real time system identification via the FTR method. It is noted from Equations 4-5 that the thrust value is needed to compute the aircraft coefficients. Thrust is not measured directly onboard the test aircraft and therefore a thrust model was developed through testing on the ground. Flight measurements of airspeed and throttle setting are used to estimate thrust with this model.

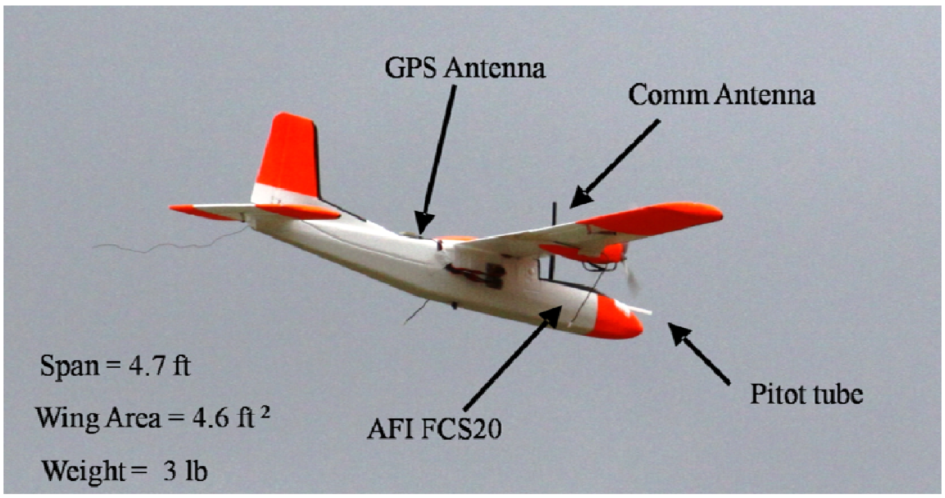

Figure 1: Multiplex Twinstar aircraft in flight and with additional instrumentation

III. System Model

A. Aircraft Dynamic Modeling

Two approaches to aircraft dynamic modeling for system identification have been used: a state-model approach and a stability coefficient approach. It is noted here that the test aircraft to be used in this study only has conventional elevator, aileron, and rudder control surfaces.

i. State-Model Approach

The state-model approach taken here is traditional and widely used. The six-degree-of-freedom aircraft equations of motion are linearized and then rearranged into matrix form as shown in Equation 1. The resulting system has eight states and three control terms. In the following, u,v,w denote the body velocity of the aircraft in the body x, y and z axes, p,q,r denote the body angular rates of the aircraft around the body x, y, and z axes. The angle of attack is given by α while β is the aircraft side slip angle. θ and ϕ are the aircraft pitch and roll angles. The actuator deflections are denoted by δ_e, δ_a, and δ_r which are elevator deflection, aileron deflection, and rudder deflection correspondingly. L,M,N and X,Y,Z denote the aircraft moments and forces around the body x, y, and z axes respectively. The subscript a/c denotes the aircraft states. Matrices A and B contain the aerodynamic stability derivatives, and the actuator effectiveness coefficients respectively. We use standard notation for modeling the aircraft, further information can be found in any standard aircraft flight dynamics book, e.g. Etkin and Reid, Dynamics of Flight Stability and Control.

$$\dot{x}_{a/c} = A_{a/c} x_{a/c} + B_{a/c} \begin{bmatrix} \delta_e \\ \delta_a \\ \delta_r \end{bmatrix} \tag{1a}$$

$$x_{a/c} = \begin{bmatrix} u & w & q & \theta & \beta & p & r & \phi \end{bmatrix}^T \quad (1b)$$

The longitudinal and lateral-directional dynamics of the state-modeled aircraft can be assumed to be decoupled for a symmetric fixed wing aircraft, and therefore the eight-state system can be decoupled into two four state systems for the longitudinal and lateral dynamics. The system identification model used for the estimation purpose is shown in Equations 2 and 3. The FTR method requires the knowledge of the left hand side (state time derivatives) of equation 1a. To improve the performance of our estimation, we use use the measurement of specific force directly from the accelerometers. These are denoted as f_x, f_y, f_z respectively.

$$\begin{bmatrix} \dot{u} \\ f_z \\ \dot{q} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} X_u & 0 & 0 & 0 \\ 0 & Z_\alpha & Z_q & 0 \\ 0 & M_\alpha & M_q & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} u \\ \alpha \\ q \\ \theta \end{bmatrix} + \begin{bmatrix} 0 \\ Z_{\delta_e} \\ M_{\delta_e} \\ 0 \end{bmatrix} \delta_e \quad (2)$$

$$\begin{bmatrix} f_y \\ \dot{p} \\ \dot{r} \\ \dot{\phi} \end{bmatrix} = \begin{bmatrix} Y_\beta & Y_p & Y_r & 0 \\ L_\beta & L_p & L_r & 0 \\ N_\beta & N_p & N_r & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \beta \\ p \\ r \\ \phi \end{bmatrix} + \begin{bmatrix} Y_{\delta_a} & Y_{\delta_r} \\ L_{\delta_a} & L_{\delta_r} \\ N_{\delta_r} & N_{\delta_r} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \delta_a \\ \delta_r \end{bmatrix} \quad (3)$$

Measurements are available for body specific force, body angular velocity, and airspeed. We use these measurements to estimate the angle of attack $\alpha = atan2(w, u)$, and the sideslip angle $\beta = \text{asin}\,(v/\sqrt{u^2 + v^2 + w^2})$. All measurements are corrected for biases and trims.

ii. Stability Coefficient Approach

The stability coefficient approach begins by computing aircraft force and moment coefficients[4] from flight measurements by using Equations 4 and 5.

$$C_X = \frac{1}{\bar{q}S}\left(ma_x - T_x\right) \quad (4a)$$

$$C_Z = \frac{1}{\bar{q}S}\left(ma_z - T_z\right) \quad (4b)$$

$$C_m = \frac{1}{\bar{q}S\bar{c}}\left[I_y\dot{q} + \left(I_x - I_z\right)pr + I_{xz}\left(p^2 - r^2\right) - M_T\right] \quad (4c)$$

$$C_Y = \frac{ma_y}{\bar{q}S} \quad (5a)$$

$$C_l = \frac{1}{\bar{q}Sb}\left[I_x\dot{p} - I_{xz}\left(pq + \dot{r}\right) + \left(I_z - I_y\right)qr - L_T\right] \quad (5b)$$

$$C_n = \frac{1}{\bar{q}Sb}\left[I_z\dot{r} - I_{xz}\left(\dot{p} - qr\right) + \left(I_y - I_x\right)pq - N_T\right] \quad (5c)$$

It is noted that the terms L_T, M_T, and N_T represent the applied moments due to thrust about each axis. For most single engine aircraft L_T and N_T are zero because the line of action of the thrust coincides with the roll axis. However since the multi-engine aircraft to be used in this study has wing-mounted engines and utilizes differential thrust as a control input these terms could in fact may be quite large and must remain.

Using linear expansions of the aircraft states and controls these expressions can then be modeled as shown in Equations 6 and 7.

$$C_X = C_{X_\alpha}\Delta\alpha + C_{X_q}\frac{\Delta q\bar{c}}{2V} + C_{X_\delta}\Delta\delta_e + C_{X_0} \quad (6a)$$

$$C_Z = C_{Z_\alpha}\Delta\alpha + C_{Z_q}\frac{\Delta q\bar{c}}{2V} + C_{Z_\delta}\Delta\delta_e + C_{Z_0} \quad (6b)$$

$$C_m = C_{m_\alpha}\Delta\alpha + C_{m_q}\frac{\Delta q\bar{c}}{2V} + C_{m_\delta}\Delta\delta_e + C_{m_0} \quad (6c)$$

$$C_Y = C_{Y_\beta}\Delta\beta + C_{Y_p}\frac{\Delta pb}{2V} + C_{Y_r}\frac{\Delta rb}{2V} + C_{Y_{\delta_a}}\Delta\delta_a + C_{Y_{\delta_r}}\Delta\delta_r + C_{Y_0} \quad (7a)$$

$$C_l = C_{l_\beta}\Delta\beta + C_{l_p}\frac{\Delta pb}{2V} + C_{l_r}\frac{\Delta rb}{2V} + C_{l_{\delta_a}}\Delta\delta_a + C_{l_{\delta_r}}\Delta\delta_r + C_{l_0} \quad (7b)$$

$$C_n = C_{n_\beta}\Delta\beta + C_{n_p}\frac{\Delta pb}{2V} + C_{n_r}\frac{\Delta rb}{2V} + C_{n_{\delta_a}}\Delta\delta_a + C_{n_{\delta_r}}\Delta\delta_r + C_{n_0} \quad (7c)$$

By equating the measured coefficient values to the linear state expansions the stability and control coefficients (C_{X_α}, C_{X_q}, etc.) can then be determined via parameter estimation since they are the only unknowns remaining. For this study there are nine longitudinal and twelve lateral stability coefficients. In this form each force or moment equation is independent and therefore this model allows flexibility for parameter estimation in that the entire system need not be included if only certain coefficients are desired, but rather just the individual equations in which the desired coefficients appear.

IV. System Identification

In this study we use the Recursive Fourier Transform Regression (FTR)[9,10] method for parameter identification.

i. Least Squares Parameter Estimation

FTR method is an extension of the Least Squares Parameter identification method in frequency domain. Least squares parameter estimation attempts to estimate unknown coefficients by performing a best-fit linear regression with measured data assuming a linear plant model. Dynamic systems governed by linear, or linearizable, equations for which the full state can be measured, or otherwise observed, are ideal candidates for plant identification via the least squares method. The aircraft dynamic model presented in Equation 1 is an example of such a system. Consider a linear model (equation 13) given where the rows of X contain measured data for each data point *k* and the rows of z contain the system outputs for each data point *k*. The vector θ are the unknown parameters. It is assumed that the parameters remain constant over the entire data set.

$$z = X\theta \quad (8)$$

The least squares cost function is then given by Equation 14.

$$J(\theta) = \tfrac{1}{2}\left(z - X\theta\right)^T\left(z - X\theta\right) \quad (9)$$

The parameter estimate which minimizes this cost function is found by minimizing the above cost function:

$$\hat{\theta} = \left(X^T X\right)^{-1} X^T z \quad (10)$$

The equation error variance is then given by Equation 16, where k is the number of rows of *X*, equations and n_p is the number of parameters to be estimated.

$$Cov(\hat{\theta}) = \frac{1}{\left(k - n_p\right)}\left(z - X\hat{\theta}\right)^T\left(z - X\hat{\theta}\right)\left(X^T X\right)^{-1} \quad (11)$$

ii. Fourier Transform Regression

Fourier Transform Regression (FTR) [9, 10] is a method developed in frequency domain for recursive parameter identification. FTR attempts to arrive at a least squares fit of the data in a recursive fashion in the frequency domain.

The Fourier transform of an arbitrary signal *x(t)* is given by:

$$F\left[x(t)\right] \equiv \tilde{x}(\omega) \equiv \int_{-\infty}^{\infty} x(t)e^{-j\omega t}\mathrm{d}t \, . \tag{12}$$

The signals of interest in this study are collected via a data sampling system so the discrete version of the Fourier transform is required. The discrete Fourier transform is given by Equation 9.

$$X(\omega) \equiv \sum_{i=0}^{N-1} x_i(t)e^{-j\omega i\Delta t} \tag{13}$$

Let Δt denote the sampling interval, and *N* the total number of data points, then the Euler approximation of the Fourier transform in equation 8 is given by:

$$\tilde{x}(\omega) \approx X(\omega)\Delta t \tag{14}$$

This approximation is suitable if the sampling rate (1/Δt) is much higher than any of the frequencies of interest (ω). This is the case in this study, as will be shown in this paper, so therefore no correction terms are needed. The discrete version of the Fourier transform can be propagated in a recursive manner, for a data point index *k,* the Fourier transform can be propagated as follows:

$$\mathrm{X_k}(\omega) = X_{k-1}(\omega) + x_k(t)e^{-j\omega k\Delta t}. \tag{15}$$

This recursive implementation greatly facilitates real time implementation.
Consider a standard regression problem with complex data, where $\tilde{Y}(w)$ denotes the dependent variable, $\tilde{X}(\omega)$ denotes the independent variables, $\tilde{\epsilon}$ denotes the regression error in the frequency domain, and Θ denotes the unknown parameters containing the aerodynamic derivatives and the actuator effectiveness parameters appearing in matrix A and B in equation 1.

$$\tilde{Y}(w) = \tilde{X}\Theta + \tilde{\epsilon} \tag{16}$$

Referring to equation 13, The matrix of dependent and independent variables is given as:

$$\tilde{X}(w) = \begin{bmatrix} \tilde{x}^T(1) & \tilde{u}^T(1) \\ \tilde{x}^T(2) & \tilde{u}^T(2) \\ \vdots & \vdots \\ \tilde{x}^T(m) & \tilde{u}^T(m) \end{bmatrix} \quad and\ \tilde{Y} = \begin{bmatrix} \tilde{z}(1) \\ \tilde{z}(2) \\ \vdots \\ \tilde{z}(m) \end{bmatrix} \tag{17}$$

Where 1..m denote the frequency band of interest over which the Fourier transform is to be calculated. Fourier transform can be calculated in a recursive manner as described in equation 11. For the purpose of this paper, we note that $\tilde{x}$ denotes the Fourier transform of the state vector, $\tilde{u}$ denotes the Fourier transform of the inputs. The dependent variable z should be considered as the left hand side of equation 2 and 3. Where measurements are available (for example the specific forces), they are directly used. If a derivative of a state signal is required, it can be easily calculated by multiplying the Fourier transform of the state with $j\omega$. FTR method attempts to minimize the following cost function in the least squares sense:

$$J = \frac{1}{2}\left(\tilde{Y} - \tilde{X}\Theta\right)^*\left(\tilde{Y} - \tilde{X}\Theta\right) \tag{18}$$

The least squares estimate for the parameter vector Θ is given by:

$$\hat{\Theta} = \left[Re\left(\tilde{X}^*\tilde{X}\right)\right]^{-1} Re(\tilde{X}^*\tilde{Y}) \tag{19}$$

where $*$ denotes the complex conjugate transpose operator. The standard deviation of the estimates can be found by taking the square root of the covariance matrix:

$$cov(\hat{\Theta}) = E\left[(\hat{\Theta} - \Theta)(\hat{\Theta} - \Theta)^T\right] = \sigma^2\left[Re(\tilde{X}^*\tilde{X})\right]^{-1} \tag{20}$$

where the equation error covariance σ^2 can be estimated as follows:

$$\sigma^2 = \frac{1}{m-n_p}\left[(\tilde{Y} - \tilde{X}\hat{\Theta})^*(\tilde{Y} - \tilde{X}\hat{\Theta})\right]. \tag{21}$$

where m is the number of frequencies over which the Fourier transform has been calculated, and n_p is the number of unknown parameters.

The FTR method has the following compelling advantages:

- FTR does not require any tuning parameters (as opposed to EKF, UKF based methods),
- Trim condition and zero biases can be inherently removed from affecting the estimation by omitting the zero frequency, similarly, high frequency content can be omitted to alleviate noise effects,
- No starting values of parameters are necessary, although starting information can be used.
- FTR has inherent memory through recursive Fourier transform

On the other hand, a forgetting factor is necessary for discounting old data when aircraft dynamics change. It should be noted that FTR assumes accurate full state knowledge and is only applicable to linear equations.

III. Data Processing

ii. Filters

Filters are used for reducing noise from the data as well as eliminate undesired or unnecessary frequency content from a signal. A fourth-order Butterworth filter is used in this study. The Butterworth filter design has been selected because its frequency response is as flat as mathematically possible in the pass-band, which is desirable since any artificial alterations to the frequency profile in the region of interest of a signal would affect the subsequent system identification results. The order of the filter has been chosen to match the system type to ensure adequate roll-off in the stop-band. It is noted that the aircraft dynamic model is a composed of two decoupled fourth-order systems, a longitudinal model and a lateral-directional model.

The Butterworth filter is an infinite impulse response filter and therefore its discrete implementation is given by the difference equation in Equation 12, where **x** is the raw signal, **y** is the filtered signal, K-1 is the filter order, and **a** and **b** are the filter coefficients.

$$y_n = \frac{1}{a_0}\left(\sum_{i=0}^{K} b_i x_{n-i} - \sum_{j=0}^{K} a_j y_{n-j}\right) \tag{12}$$

Real-time implementation of the filter is straightforward, but it is important to note that the last K samples of both the raw and filtered signals must be retained in memory to do so.

iii. Data Analysis

Data analysis prior to system identification serves to identify three characteristics of the system response: frequencies present, time required to isolate dominant frequencies, and variability of frequency content with time.

A custom spectrogram tool was designed and then implemented for analyzing the time frequency content of data used for system identification. The spectrogram tool utilizes the finite Fourier transform methods already presented in this paper and can operate on both real-time and batch-stored data signals. Using this tool, it was determined that the frequency range of interest lies between 0 and 3 Hz.

IV. Recursive Parameter Identification Results

In this section we describe the results from recursive parameter identification using FTR method. The purpose of this paper is to assess the feasibility of using FTR for real time parameter identification onboard the Twinstar. For that purpose, flight data was used for system identification in a recursive fashion in MATLAB post-flight.

A. Data Gathering

In order to ensure fast convergence a series of optimized inputs has been suggested in [9]. We excite the elevator, aileron, and the rudder channel using a sum of sines input. Phase angles are optimized so that the three inputs are orthogonal and optimized to have rich inputs without having high amplitude peaks. The specific inputs used are presented in Figure 7. Injecting such a sequence of inputs while in flight is termed as a system identification maneuver. An interesting point to note is that since GT Twinstar is a UAV these inputs were performed under closed loop condition. That means, the UAV was in active control when these inputs were injected onto the control surfaces. This allowed us to maintain flight velocity and retain stability in presence of external disturbances. It should be noted however, that the input deflection used for the purpose of gathering system identification data are much larger than nominal input deflections required by the autopilot to maintain steady level flight.

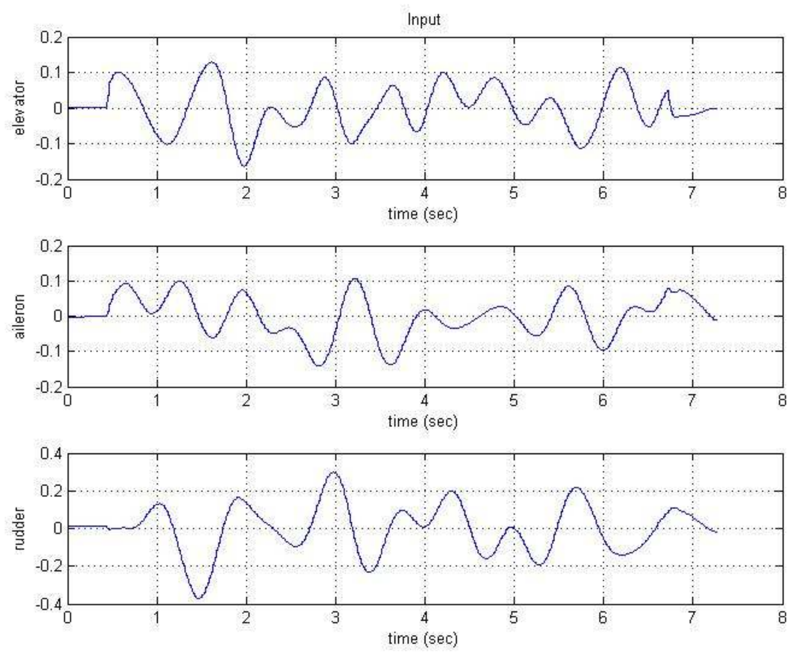

Figure 7: *Flight-test system identification inputs, units are scaled within -1 and 1*

B. System Identification Results

The time-domain least squares parameter estimation algorithm results are presented first. Figures 8 and 9 show the comparison of estimated model output with measured data. The time domain least squares estimation serve to validate the linear model and to set nominal parameter values.

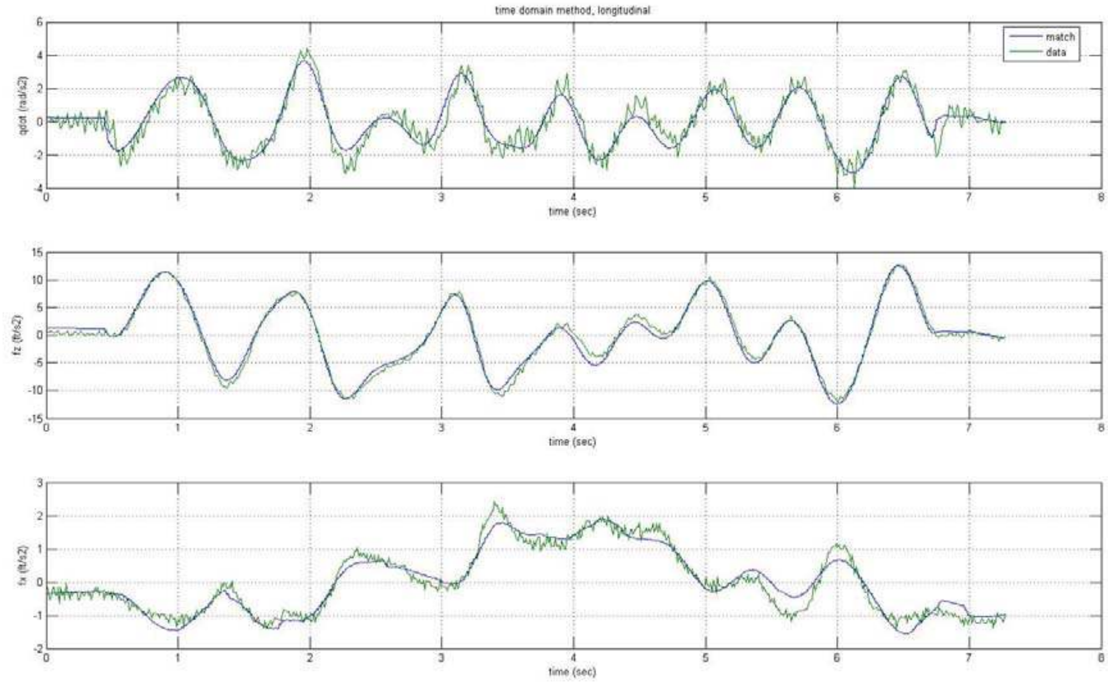

Figure 8: *Longitudinal time-domain parameter estimate model match compared with measured flight test data*

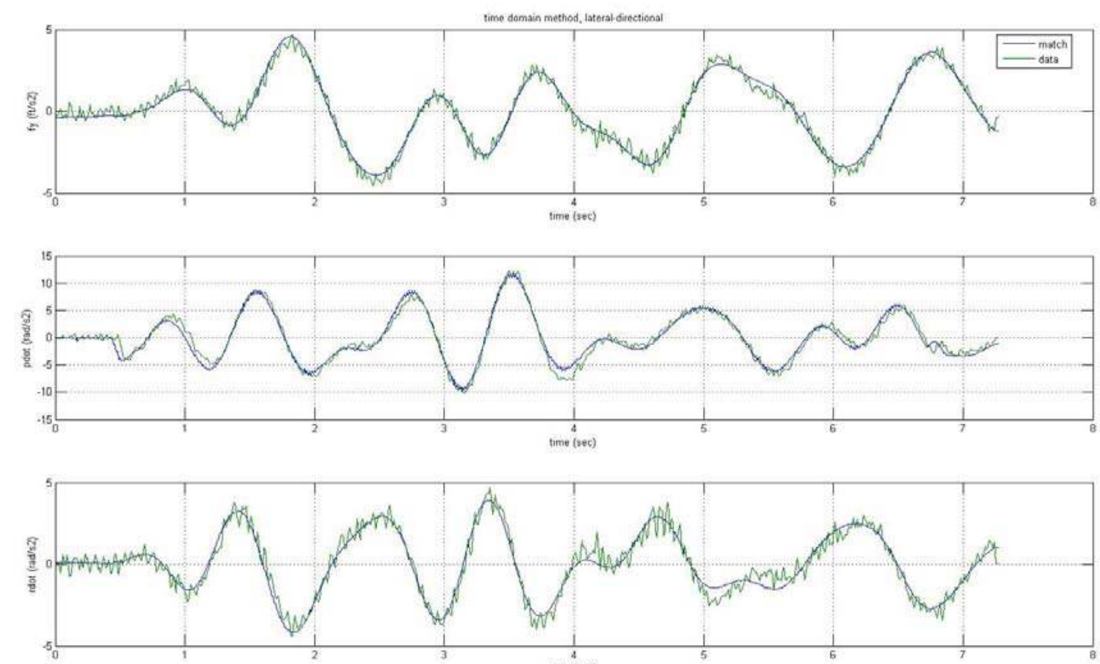

Figure 9: *Lateral-directional time-domain parameter estimate model match compared with measured flight test data*

The FTR method results are now presented. Both the longitudinal and lateral-directional dimensional stability derivatives of the aerodynamic forces and moments were estimated. Figures 10-14 show the real-time parameter estimates as they converge over time and the associated 2σ variance. It should be noted that the system identification maneuver starts after around 0.5 seconds into the flight. Considering this, it is seen that parameters begin to converge withing 2 seconds of starting the system identification maneuver. Additionally, the numeric values of the aerodynamic derivatives at the end of the run are summarized in table 2 for both the longitudinal and lateral equations. The estimated values fall within a tolerable region of the values estimated from batch processed data using least squares estimation, which are also given in the table.

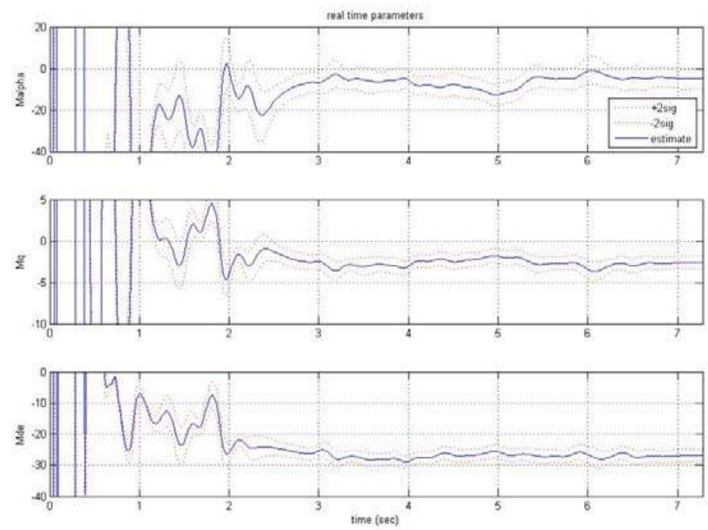

Figure 10: *FTR stability derivative estimates from flight test data, pitching moment*

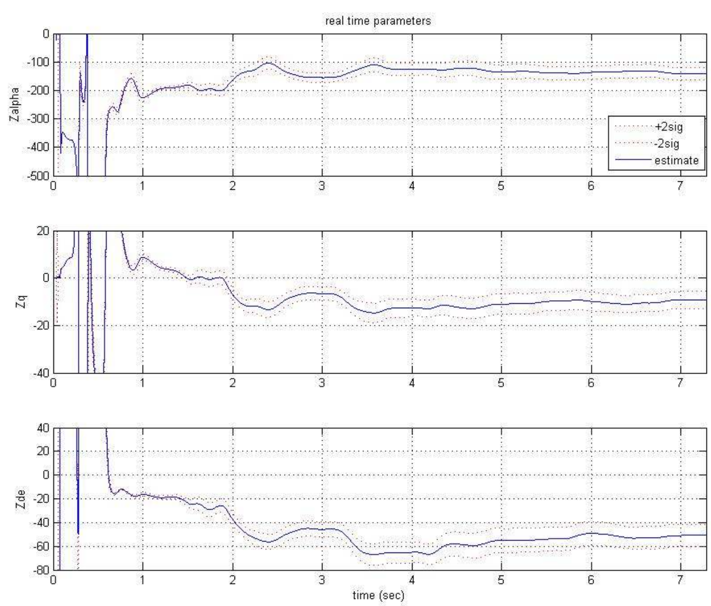

Figure 11: *FTR stability derivative estimates from flight test data, vertical force*

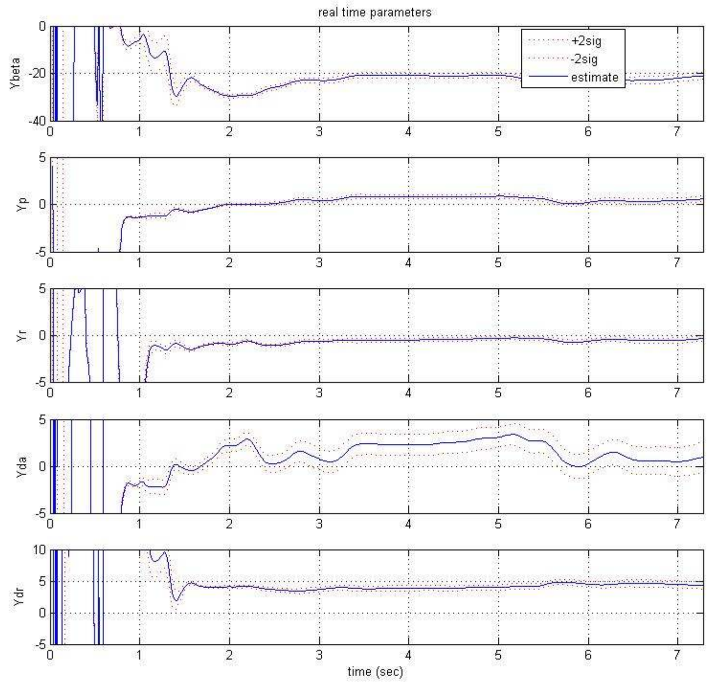

Figure 12: *FTR stability derivative estimates from flight test data, lateral force*

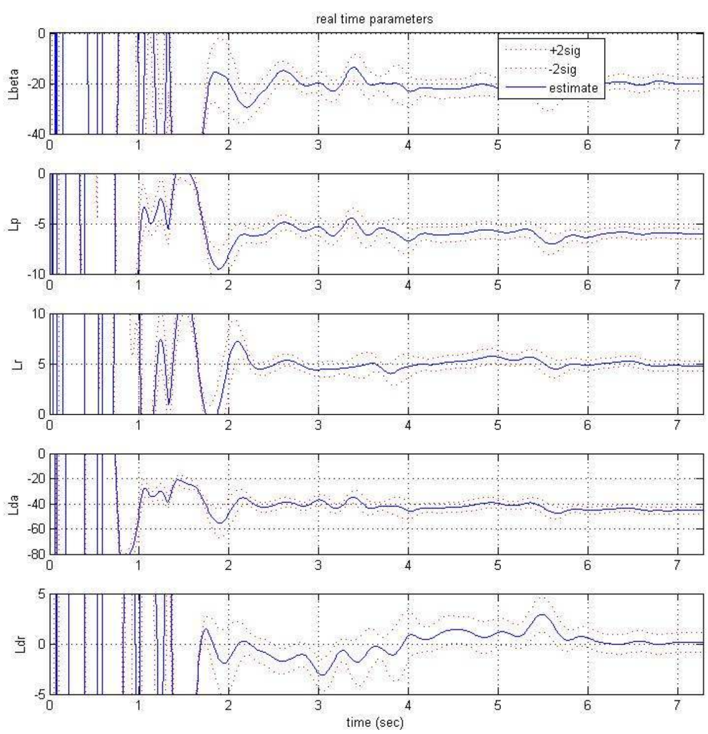

Figure 13: *FTR stability derivative estimates from flight test data, rolling moment*

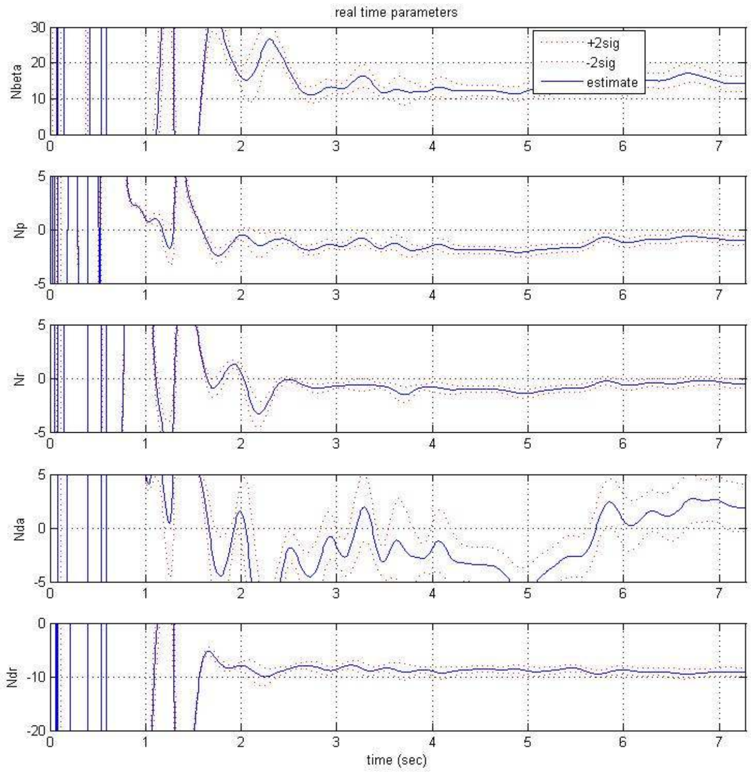

Figure 14: *FTR stability derivative estimates from flight test data, yawing moment*

Table II: *Final values of parameter estimates using FTR with flight test data .*

Parameter Name	Estimated Value (FTR)	Standard deviation (2-sigma)	Estimated value using batch processing Least squares
M_α	-4.94	2.43	-4.46
M_q	-2.62	0.40	-2.54
$M_{\delta e}$	-26.88	1.04	-26.13
Z_α	-140.33	10.96	-114.77
Z_q	-9.28	1.79	-12.28
$Z_{\delta e}$	-50.76	4.70	-55.42
Y_β	-21.02	0.77	-20.23
Y_p	0.58	0.15	0.72
Y_r	-0.38	0.14	-0.24
$Y_{\delta a}$	0.97	0.80	1.3
$Y_{\delta r}$	4.37	0.30	4.42
L_β	-20.25	1.31	-19.95
L_p	-6.01	0.26	-5.85
L_r	4.77	0.24	5.22
$L_{\delta a}$	-45.43	1.36	-44.73
$L_{\delta r}$	0.15	0.50	0.64
N_β	14.26	1.04	13.24
N_p	-1.02	0.20	-1.18
N_r	-0.50	0.19	-0.57
$N_{\delta a}$	1.8823	1.08	2.34
$N_{\delta r}$	-9.11	0.40	-9.09

C. Frequency domain validation

Since frequency-domain data is the core of the FTR method, the frequency content of the estimated model was compared to the frequency content of the measured data to ensure a match of the estimated model to the actual dynamics. This is achieved by comparing the measured data and the model output in the frequency domain as a function of frequency. Figures 15 and 16 show the absolute value of the discrete Fourier transform coefficients, and as can be seen the model match is close over all frequencies. Furthermore, the results confirm the expectation that maximum activity occurs in the 0.5 to 2 Hz frequency band.

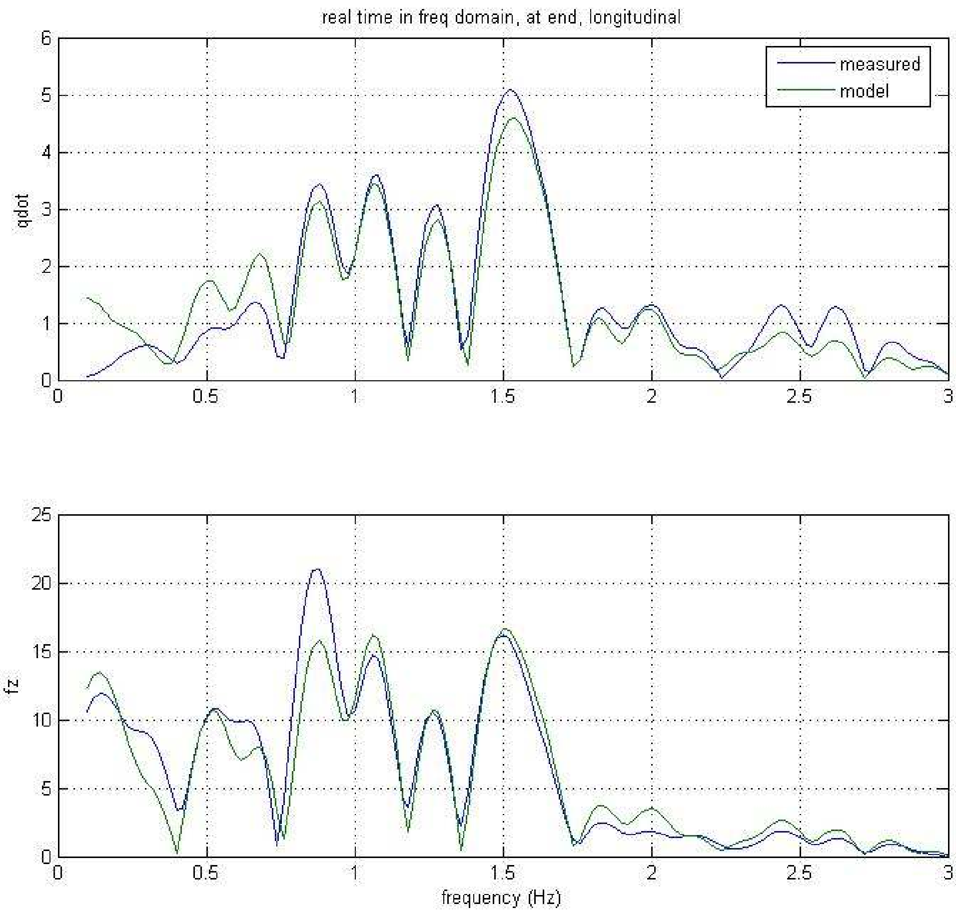

Figure 15: *Frequency content of FTR estimated model compared to measured data, longitudinal*

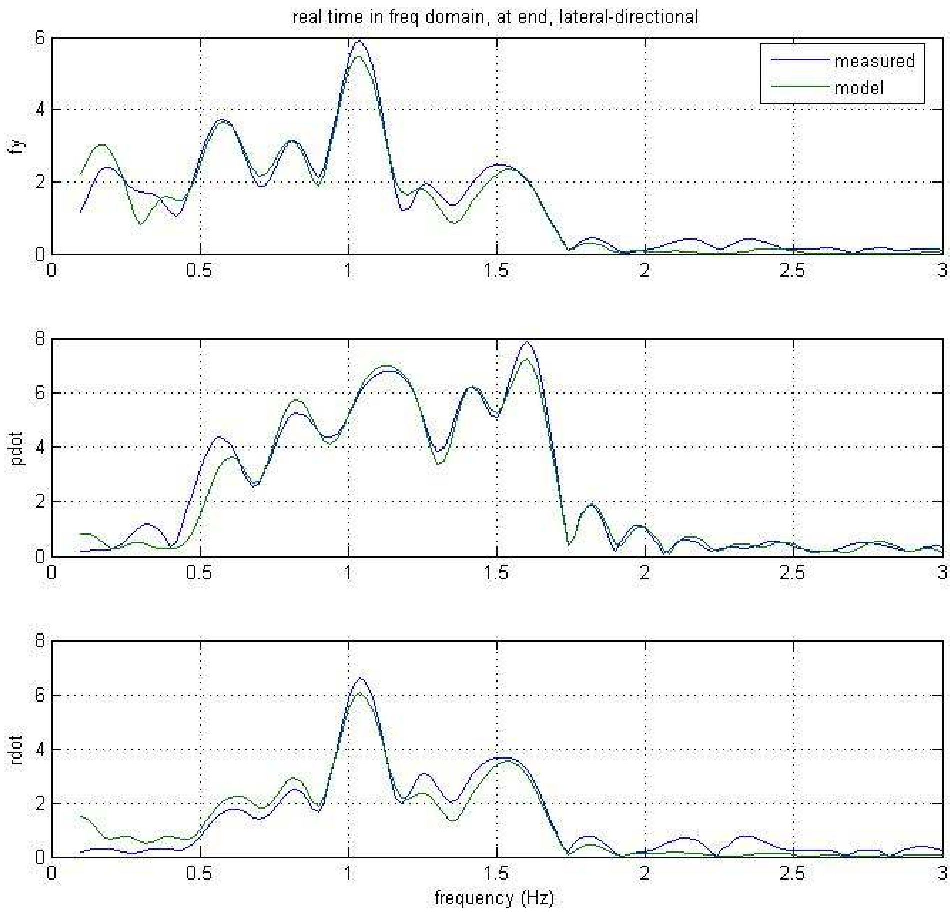

Figure 16: *Frequency content of FTR estimated model compared to measured data, lateral-directional*

D. Validation in time domain using data not used for flight test

The parameter estimates obtained using the recursive FTR method were validated in time domain for data not used for system identification and the match was found satisfactory.

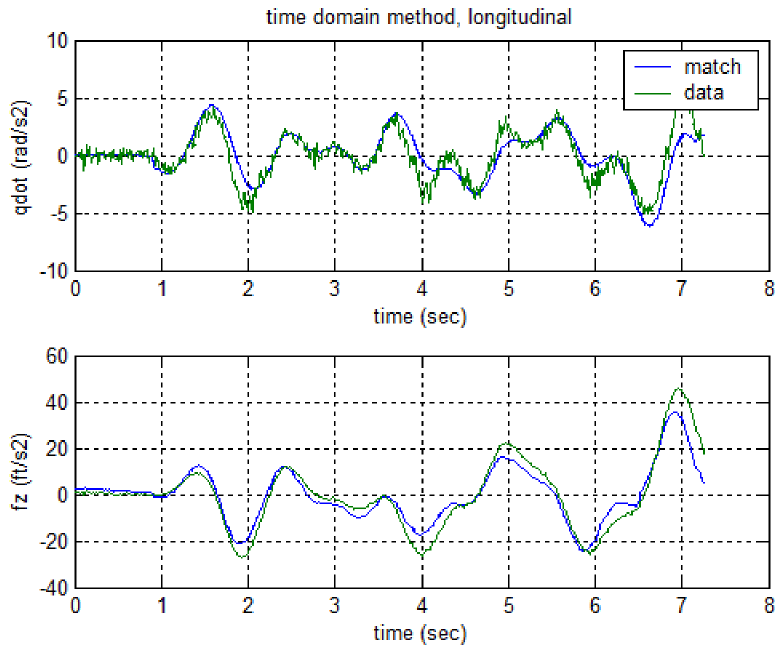

Figure 17: *Longitudinal equations time domain validation using data not used for system identification,*

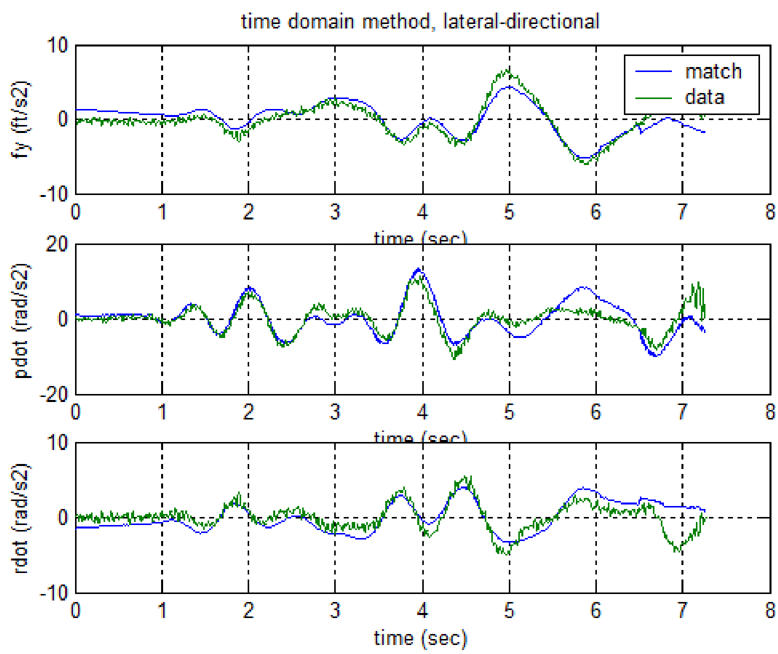

Figure 18: *Lateral equations time domain validation using data not used for system identification,*

V. Conclusion

In this paper, optimized multi sine inputs were used for gathering rich system identification data. Recursive implementation of FTR method with a recursive Butterworth filter was used for parameter identification Our results indicate satisfactory parameter convergence and good time domain as well as frequency domain match. Our results also validated the assumption that a simple linear model is sufficient for capturing the behavior of the GT Twinstar. It should be noted however, that heavy damage or extremely aggressive maneuvers could lead to build up of nonlinear effects.

The method used in this paper was analyzed for computational requirements and it was found that it would be possible to implement this method in real time on the AFI FCS 20 autopilot. These results indicate the feasibility of using the FTR method for real time parameter on a fixed wing twin engine UAV.

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