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Real-time Parameter Estimation for Reconfigurable Control of Unstable Aircraft

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ABSTRACT

The real-time open-loop parameter estimation of unstable/augmented aircraft is essential for reconfigurable/adaptive control. This paper describes two parameter estimation algorithms based on the equation-error minimisation principle. One is the recently developed, well-established recursive discrete Fourier transform (DFT) technique in frequency domain. The other is an application of recursive least square (RLS) in equation[2] error minimisation concept, applied to unstable/augmented aircraft parameter estimation. The RLS technique reported in this paper is implemented, for the first time, by a methodology that is analogous to the recursive DFT technique. Hence, in time domain, this can be viewed as a counter part of recursive DFT. The algorithms are implemented and tested for robustness against measurement noise. For the implementation, initially, data was generated under realistic conditions from simulation software that captures the dynamics of an unstable high performance aircraft, which is stabilised by full authority control laws. Subsequently, the algorithms are also tested with real flight data of a high performance unstable augmented fighter aircraft. The results bring out the merits of the algorithms and show their suitability for modelling of unstable aircraft, for subsequent adaptive/reconfigurable control or fault diagnosis.

Keywords: Real-time parameter estimation, adaptive/reconfigurable control, equation error, discrete Fourier transform, recursive least squares, digital filtering

NOMENCLATURE

A	System matrix
B	Control matrix
$E\{\}$	Expectation operator
H	Filter transfer function
J	Cost function
m	Total number of discrete frequency points
N	Total number of discrete observations
P	Covariance matrix
Re	Real part
p	Number of unknown parameters
q	Pitch rate
t	Time
v	Measurement noise
α	Angle of attack
β	Unknown parameter vector

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ε Equation error

λ Forgetting factor

ω Frequency

δ_e Elevator control surface input

$x(t)$ State vector

$y(t)$ Observation vector

Δt Sampling time

σ^2 Equation error variance

$\dagger$ Complex conjugate transpose

1. INTRODUCTION

Improved aircraft survivability and robustness of aircraft responses to faulty operating conditions together form the goal of modern flight control research. The emphasis on diagnosis of faults during a flight leads to the study of adaptive/reconfigurable control. The adaptive/reconfigurable control schemes require the identification of a mathematical model of aircraft and use the identified dynamics to reconfigure the controller and achieve the desired aircraft responses in the presence of failure. Real-time parameter techniques play significant role in identifying the post failure mathematical models of aircraft. Real-time parameter estimation working within (an adaptive) control scheme is a more challenging and demanding task. The desirable features of such estimation algorithms are: (i) faster convergence, (ii) less computational complexities and onboard memory, and (iii) no starting guess and tuning parameters. The extended Kalman filter (EKF)/UD factorisation-based extended Kalman filter (UDEKF) could be potentially used for online parameter estimation of unstable/augmented aircraft[1,2] but at an increased computational complexity. The filter error, output error with artificial stabilisation and multiple shooting methods could be used only in batch for parameter estimation of unstable aircraft[3]. The extended forgetting factor recursive least squares (EFRLS) has been extensively used in aircraft joint state and parameter estimation[4] but is again a variant of Kalman filter.

This paper presents the results of two algorithms that satisfy some or all of the foregoing requirements of good estimator for modelling of a plant for an adaptive control: (i) a well-established recursive DFT technique in frequency domain, and (ii) RLS in time domain. The application of RLS in this paper is extended to minimise the equation error aiming only at parameter estimation. This requires the accurate measurements of states and state derivatives. The state derivatives are computed online with a digital filter that combines the role of a differentiator and a low-pass filter. Hence, this novel application of well-established RLS is analogous to recursive DFT, applied for unstable/augmented aircraft parameter estimation, perhaps, for the first time. The implementation results of recursive DFT and RLS as applied to unstable/augmented aircraft parameter estimation has been presented. A comparative study is also carried out to evaluate the performance of these methods. For the implementation, initially, required data were generated using flight simulation software named LSIM_version_0.2.7 (developed at NAL[5]). Subsequently the algorithms were validated with real-flight data of a high performance, unstable fighter aircraft that was highly augmented.

2. PARAMETER ESTIMATION FOR UNSTABLE/AUGMENTED AIRCRAFT

The block diagram of Fig. 1 shows the schematic of an unstable augmented aircraft. The present study considers a high performance delta wing fighter aircraft. It has four elevons and rudder as primary control surfaces. The elevator and aileron control effects are achieved by deflecting elevons together and in differential mode. This aircraft is open loop unstable. The aircraft is stabilised with a highly augmented feedback control law. The flight simulation software LSIM_version_0.2.7 is capable of generating the linear open-loop models and simulating the closed-loop responses of this class of aircraft. From Fig. 1, it is clear that the pilot input is different from the control-surface input due to the presence of feedback and actuator dynamics. The control law changes open-loop behaviour of the aircraft significantly. Hence, in such cases, using the control surface input and closed-loop responses, it becomes difficult to estimate the open-loop parameters of the aircraft[1,2]. For the present study, a flight

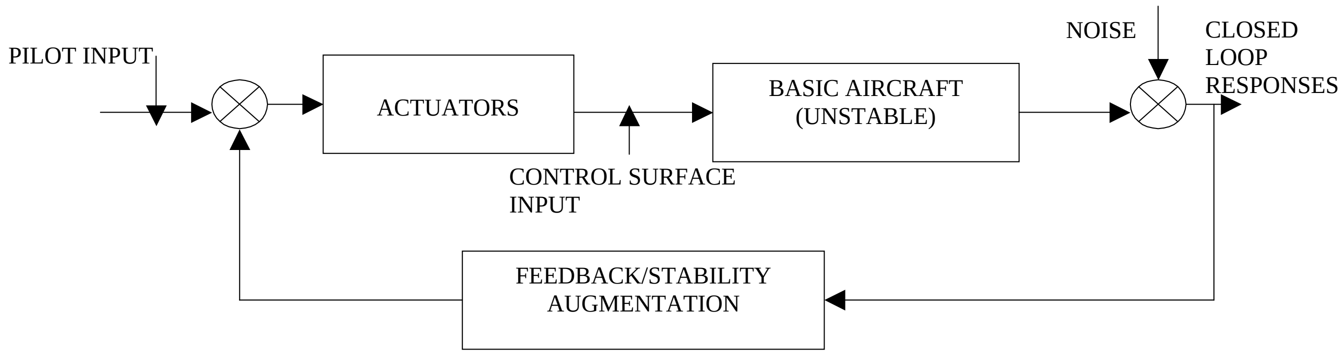

Figure 1. Block diagram of unstable/augmented aircraft.

condition with Mach No. = 0.22, altitude = 300 m, fuel state = 9060, landing gear retracted and automatic slat was used to simulate the short period data from LSIM software. The open-loop aircraft is unstable at this flight condition. Subsequently, the recorded flight data of a high performance unstable augmented aircraft for a flight condition of Mach No. = 0.7 and altitude = 4119 m has been used to establish the use of the algorithms for the real flight data.

2.1 Short Period Mathematical Model

The short period mathematical model consists of two states namely angle of attack (α) and pitch rate (q). The control surface input is δ_e. The state equations are represented in the matrix form as:

$$\begin{bmatrix}\dot{\alpha}\\ \dot{q}\end{bmatrix}=\begin{bmatrix}Z_\alpha & Z_q\\ M_\alpha & M_q\end{bmatrix}\begin{bmatrix}\alpha\\ q\end{bmatrix}+\begin{bmatrix}Z_{\delta e}\\ M_{\delta e}\end{bmatrix}\delta_e \tag{1}$$

The numerical values of the parameters for comparing against results from estimation algorithm are given by

$$\begin{bmatrix}\dot{\alpha}\\ \dot{q}\end{bmatrix}=\begin{bmatrix}-0.4784 & 0.9724\\ 0.5160 & -0.4276\end{bmatrix}\begin{bmatrix}\alpha\\ q\end{bmatrix}+\begin{bmatrix}-0.1842\\ -3.7391\end{bmatrix}\delta_e \tag{2}$$

The eigen values for this plant are: –1.1618 and 0.2558. Here, 0.2558 is an unstable pole.

2.1 Recursive Discrete Fourier Transform

The aircraft longitudinal and lateral dynamics can be approximated by the following continuous-time state variable model as

$$\begin{aligned}\dot{x}(t)&=Ax(t)+Bu(t)\\ x(0)&=x_0\\ y(t)&=x(t)\end{aligned} \tag{3}$$

The application of the Fourier transform (FT) to aircraft state variable model will yield[6,7]

$$\begin{aligned}j\omega\tilde{x}(\omega)&=A\tilde{x}(\omega)+B\tilde{u}(\omega)\\ \tilde{y}(\omega)&=\tilde{x}(\omega)\end{aligned} \tag{4}$$

Using the least squares (LS) regression method, the measurements of the vector x and u can be used to set up a cost function having the coefficients A, B as argument. The standard squared error cost function in the frequency domain is written as

$$J_k=\frac{1}{2}\sum_{n=1}^{m}|j\omega_n\,\tilde{x}_k(\omega_n)-A_k\,\tilde{x}(\omega_n)-B_k\,\tilde{u}(\omega_n)|^2 \tag{5}$$

$$=\frac{1}{2}(Y-X\beta)^{\dagger}*(Y-X\beta)` \tag{6}$$

The sub-optimal parameter vector estimate is written as

$$\hat{\beta}=[\mathrm{Re}(X^{\dagger}*X)]^{-1}\,\mathrm{Re}(X^{\dagger}*Y) \tag{7}$$

In addition, the covariance matrix of $\hat{\beta}$ is computed as

$$\mathrm{cov}(\hat{\beta})=E\{(\hat{\beta}-\beta)(\hat{\beta}-\beta)^T\}=\sigma^2[\mathrm{Re}(X^{\dagger}*X)]^{-1} \tag{8}$$

where σ is the equation error variance and it can be estimated online using

$$\sigma^2 = \frac{1}{(m-p)}[(Y - X\hat{\beta})^\dagger * (Y - X\hat{\beta})] \quad (9)$$

Furthermore, the standard deviation of the estimation error for the k^{th} unknown of the p parameters in β can be evaluated as the square root of the (k,k) main-diagonal coefficient of the covariance matrix. The standard deviation allows an online assessment of the accuracy of the estimated parameter.

2.2 Recursive Least Squares

As before, the aircraft longitudinal and lateral dynamics can be approximated by Eqn (3). The discrete time observation can be represented as

$$Z_i = y_i + v_i, \; i = 1,2,....,N \quad (10)$$

where N is the total number of observations.

At any discrete time $t = n$, assemble

$$\begin{aligned} X &= [x_1(n)\;\; x_2(n) \ldots x_k(n)\; u_1(n)\; u_2(n) \ldots u_k(n)] \\ Y &= [\dot{x}_1(n)\;\; \dot{x}_2(n) \ldots \dot{x}_k(n)] \\ \beta &= [A\; B] \end{aligned} \quad (11)$$

Hence, the state equation at any discrete time can be represented as

Y = X β + ε

Thus, the problem of parameter estimation in time domain can be formulated as a standard LS regression problem with the following cost function.

$$J = \sum_{i=1}^{N} \lambda^{N-i} |\varepsilon(i)|^2 \quad i = 1,2,...,N \quad (12)$$

where λ is forgetting factor close to 1, when λ = 1, the method reduces to ordinary least squares. The unknown parameter vector β can be estimated recursively[8] using the following steps:

Initialise the algorithm by setting $P_0 = \delta^{-1} I$, where δ is a small positive constant and $\hat{\beta}_0 = 0$. For each instant of time, n = 1,2,…,N , compute

$$\begin{aligned} \pi_n &= X_n P_{n-1} \\ \kappa_n &= \lambda + \pi_n X_n{}^T \\ k_n &= P_{n-1} X_n{}^T / \kappa_n \\ \alpha_n &= Y_n - (\hat{\beta}_{n-1} X_n{}^T)^T \\ \hat{\beta}_n &= \hat{\beta}_{n-1} + (k_n \alpha_n)^T \\ P'_{n-1} &= k_n \pi_n \\ P_n &= \frac{1}{\lambda}(P_{n-1} - P'_{n-1}) \end{aligned} \quad (13)$$

where P is the correlation matrix. In addition, the covariance matrix of $\hat{\beta}$ is computed as

$$\text{cov}(\hat{\beta}) = E\{(\hat{\beta} - \beta)(\hat{\beta} - \beta)^T\} = \sigma^2 P \quad (14)$$

where σ^2 is the equation error variance and can be estimated online, similar to DFT technique.

3. RESULTS OF PARAMETER ESTIMATION BY RECURSIVE DFT

The parameter estimation by recursive DFT was done for two cases:

(i) Clean data

(ii) Noisy data (SNR=10)

Here, the time domain data is converted into frequency domain data using the recursive DFT taken over a frequency range of interest. The frequency range of interest could be chosen by plotting the power spectral density plots of the measured time histories offline. It is seen from Fig. 3 that the prominent lobes of PSDs extend form 0 to 4.2 rad/s. The side lobes start from 4.2 rad/s. For parameter estimation, the prominent lobe frequency range contains all the useful information. Hence, the recursive DFT is taken over the frequency range of 0.01 to 4.2 rad/s. The zero frequency is removed to eliminate the effect of bias in the data. The number of evenly-spaced frequency points in the selected frequency range is chosen to be 50.

3.1 Clean Data

The time histories of measured clean data obtained from LSIM software are shown in Fig. 2. The corresponding power spectral density plots are shown in Fig. 3. The PSD confirms the presence of bias in the data. The convergence of estimated parameters to their true values is shown in Fig. 4. It can be seen that the convergence is achieved around 6 s. The estimated results are given in Table 1. The parameter estimation error norm in Table 1 is calculated as

$$PEEN = \frac{norm(\beta_t - \hat{\beta})}{norm(\beta_t)} * 100$$

where β_t is the vector of true parameters and $\hat{\beta}$ is the vector of estimated parameters.

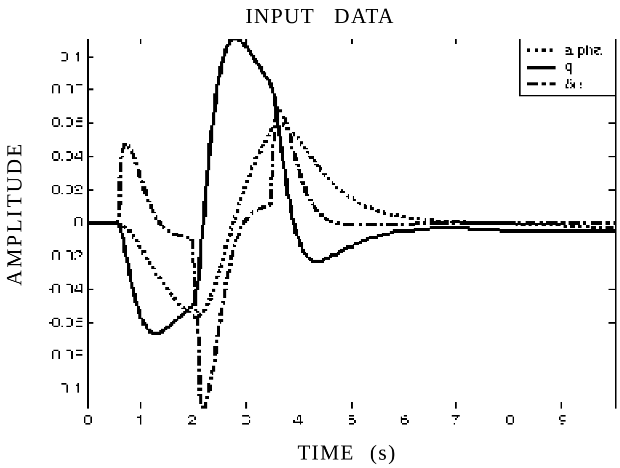

Figure 2. Time histories of measured clean data.

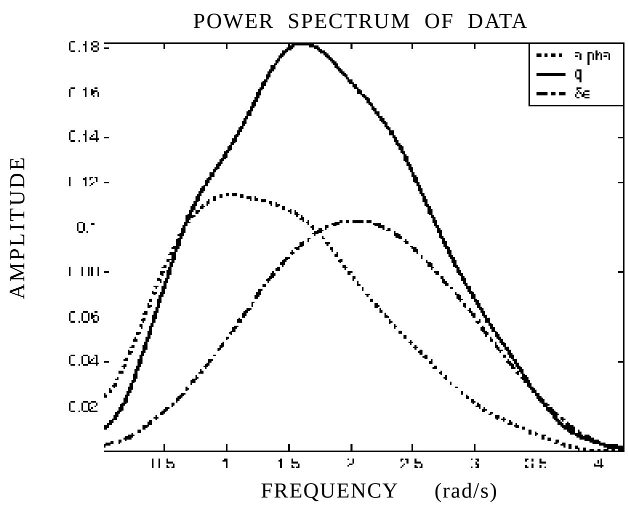

Figure 3. PSDs of clean measured time histories.

3.2 Noisy Data (SNR=10)

Random gaussian noise having SNR=10 was added to LSIM-generated time histories. The noisy time histories are shown in Fig. 5. The convergence

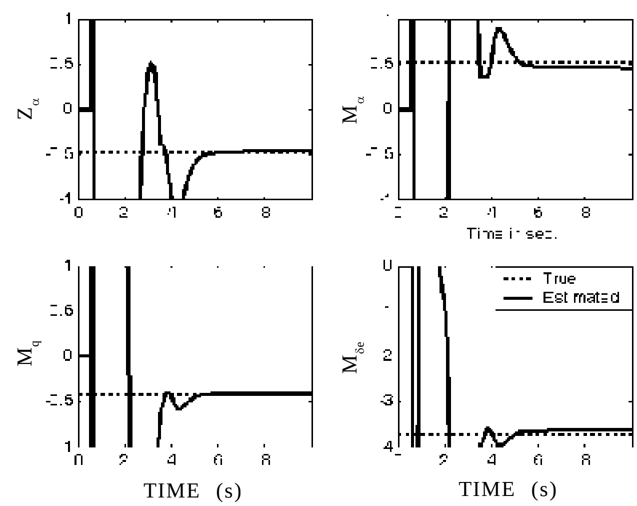

Figure 4. Convergence of recursive DFT (clean data).

Table 1. Comparison of results of frequency domain DFT with time domain RLS.

Aircraft short period parameters	True values	Case 1. Estimates from clean data				Case 2. Estimates from noisy data (SNR=10)			
		DFT		RLS		DFT		RLS	
		EST	STD	EST	STD	EST	STD	EST	STD
α	–0.4784	–0.4703	0.0272	–0.4680	0.0079	–0.3564	0.0576	–0.3853	0.0153
$M\alpha$	0.5160	0.4578	0.0218	0.4580	0.0016	0.5908	0.0650	0.5941	0.0022
M_q	–0.4276	–0.4142	0.0099	–0.4131	0.0007	–0.4723	0.0291	–0.4735	0.0010
$M_{\delta e}$	–3.7391	–3.6357	0.0224	–3.6353	0.0017	–3.7693	0.0671	–3.7764	0.0023
PEEN		**3.1241**		**3.1389**		**3.9949**		**3.5317**	

of estimated parameters to their true values is shown in Fig. 6. It can be seen that the initial oscillation of parameters are high and the convergence is achieved around 6 s. The estimated results are given in Table 1.

3.3 Monte Carlo Analysis

The results of Table 1 for the noisy data were obtained with one particular seed number. Therefore, these results could change with different seed numbers. In order to check the robustness of the algorithm for noisy data with SNR=10, the algorithm was run for 500 times with varying seed numbers. Every time, the estimates were collected and finally the ensemble average results of 500 estimates have been presented in Table 2. The results are satisfactory for SNR=10.

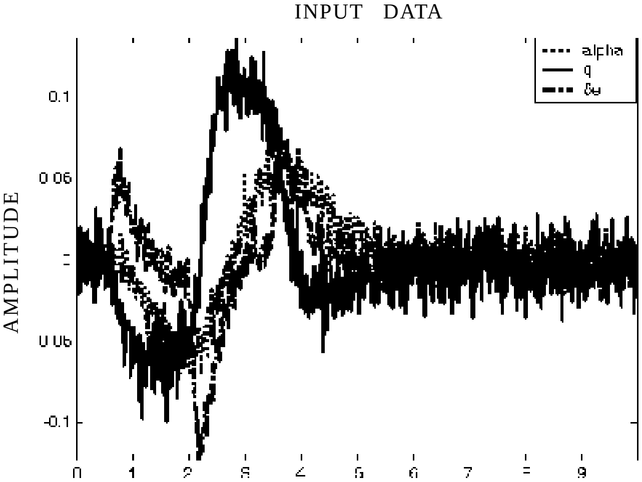

Figure 5. Time histories of noisy data (SNR=10).

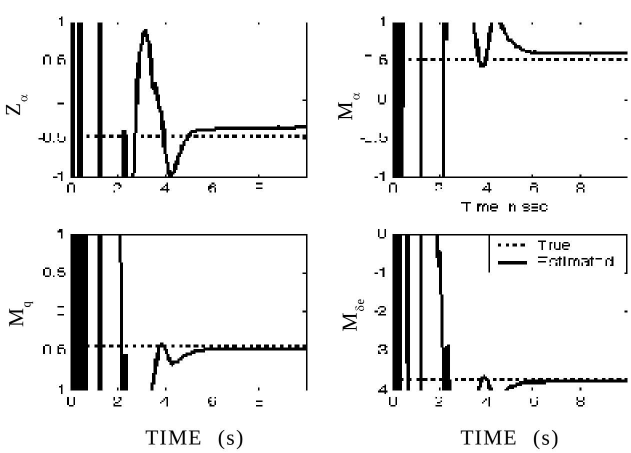

Figure 6. Convergence of DFT estimates (SNR=10).

Table 2. Monte Carlo simulation results (500 runs)

Aircraft Short Period Parameters	True values	Ensemble average of DFT estimation SNR=10	Ensemble average of RLS estimation SNR=10
Z_α	–0.4784	–0.4695	–0.4664
M_α	0.5160	0.4392	0.4376
M_q	–0.4276	–0.4027	–0.4008
$M_{\delta e}$	–3.7391	–3.6134	–3.6105
PEEN		**3.9078**	**4.0068**

4. RESULTS OF PARAMETER ESTIMATION BY RLS

The parameter estimation by RLS was carried out with the same set of data as used in the Section 3. This method requires state derivatives to be available online. In this study, this is accomplished using a digital filter that combines the role of differentiator and a second order-low pass-filter. This filter removes the high frequency noise as the measurement state variables might be noisy and differentiation enhances noise further. The cutoff frequency for the low-pass filter is chosen based on the half time period width of the doublet-pitch stick input. Throughout this study, the half time period of pitch stick, doublet input was chosen to be 1.5 s. The corresponding filter frequency was approximately 4.2 rad/s. It can be noted that range of frequency interest in recursive DFT was also 0.01– 4.2 rad/s. Hence, there is an analogy between the procedures adopted to implement the two techniques.

The analog equivalent of the digital filter combining the role of differentiator and low–pass filter is

$$H = \frac{s}{s^2 + \sqrt{2}s + 1} \tag{15}$$

Application of digital filtering to state derivatives introduces time lag, so that other measured time histories like the state variables and control inputs must be identically filtered to avoid time shifting of data[9]. The analog equivalent of the digital filter performing only the low-pass filtering is

$$H = \frac{1}{s^2 + \sqrt{2}s + 1} \tag{16}$$

Since, the present study assumes stationary data, the forgetting factor is chosen to be 1. The small positive constant δ is chosen to be 0.00001. The recursion is started with $\hat{\beta} = 0$.

4.1 Clean Data

The state derivatives were online computed using filter Eqn (15). To produce equal lag in other state and control signals, filter Eqn (16) was used. The convergence of estimated parameters to their true values is shown in Fig. 7. It can be seen that the convergence of estimates is less oscillatory compared to that of DFT estimates. Convergence of DFT estimates shows large initial transients as can be seen from Fig. 4. Most evidently, the final convergence of estimates of RLS happens around 3 s which is again faster than the convergence of recursive DFT technique, as shown in Fig. 4. Faster convergence of important parameters like M_α and $M_{\delta e}$ is a desirable feature in aircraft control. This is achieved in RLS as can be confirmed from Fig. 7. The faster convergence of RLS is due to the fact that, it makes use of Hessian for updating the parameter estimate and also direct time domain data has been used without any transformations. The slow convergence of DFT is due to the fact that, at least 6 s duration time domain data is required, to gain sufficient information content, for estimation in frequency domain. Hence, the transformation of time domain data to frequency domain affects convergence characteristics. The estimated results are given in Table 1.

4.2 Noisy Data (SNR=10)

The parameter estimation was carried out with noisy data following the same steps as mentioned in the previous section. Convergence of estimates to their true values is shown Fig. 8. Again, it can be seen that the convergence of estimates is less oscillatory compared to that of DFT estimates. The large initial transients of DFT estimates can be seen from Fig. 6. The convergence of RLS estimates happens around 3 s, which is again faster than the convergence of DFT estimates presented in Fig. 6. Even with noisy data assumption, RLS provides faster convergence of M_α and $M_{\alpha e}$ that can be confirmed from Fig. 8. The results are presented in Table 1.

4.3 Monte Carlo Analysis

As discussed before, to check the robustness of the algorithm for noisy data having SNR=10, the algorithm was run for 500 times with different seed numbers. The ensemble average results of 500 estimates are presented in Table 2. The results are satisfactory for SNR=10.

5. ALGORITHMS FOR REAL FLIGHT DATA OF A HIGH PERFORMANCE UNSTABLE AUGMENTED AIRCRAFT

The real short period flight data of a high performance unstable augmented fighter aircraft

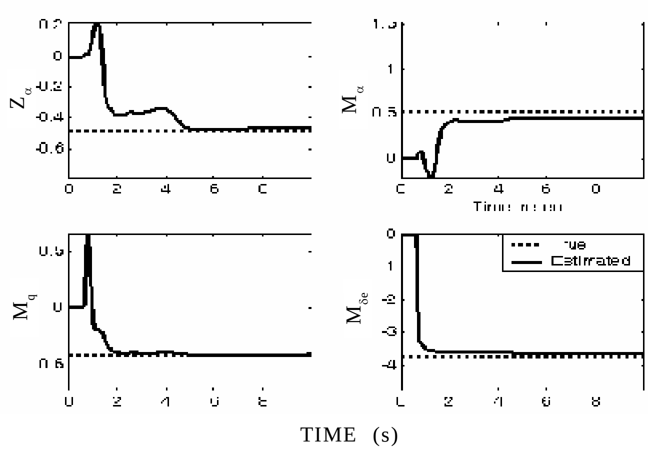

Figure 7. Convergence of RLS estimates (clean data).

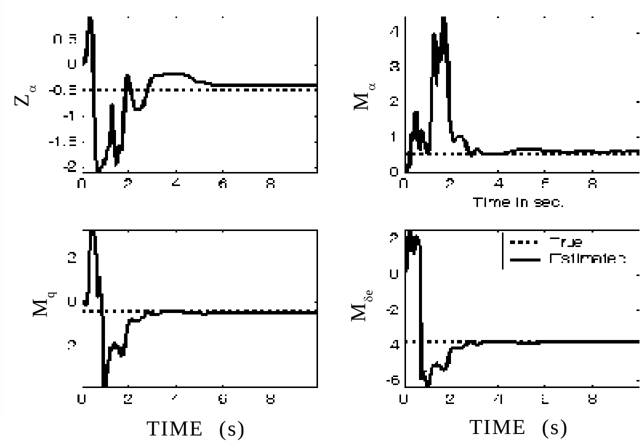

Figure 8. Convergence of RLS estimates (SNR=10).

Table 3. Parameter Estimation for real flight data

Aircraft short period parameters	DFT estimates	RLS estimates
Z_α	–0.9093	–0.8969
M_α	–1.5278	–1.5406
M_q	–1.0404	–1.0208
$M_{\delta e}$	–12.5710	–12.5810

has been used to test the algorithms. The data has been recorded for a flight condition of Mach No. = 0.7 and altitude 4119 m. The flight data is shown in Fig. 9. The DFT technique has been used as a basis for verifying the RLS estimates. The convergence of RLS estimates along with DFT estimates and vice-versa have been shown in Fig. 10. It can be noted that the convergence of RLS is faster than DFT technique for the flight data. To check the validity of the estimated short period model, the states are simulated by applying the flight elevator control surface input to the estimated model. The plots having the comparison of flight recorded time histories with simulated time histories have been shown in Fig. 11. A comparison having the estimates of DFT and RLS for the real flight data has been shown in Table 3.

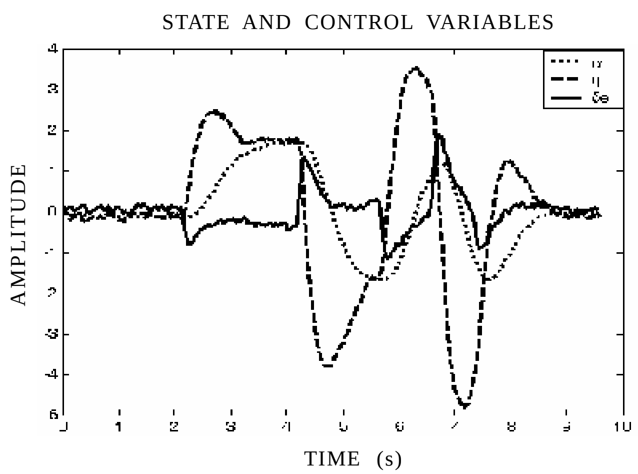

Figure 9. Real flight short period data.

6. COMPARISON OF RLS WITH RECURSIVE DFT

From the above discussions, it is apparent that the RLS, is analogous to recursive DFT. In RLS digital filtering of measured time histories is achieved by choosing cut-off frequency as 4.2 rad/s. Since the recursive DFT is also takenover a frequency range of 0.01–4.2 rad/s this achieves similar kind of filtering in frequency domain technique. Even though both methods are converging closer to the true values of parameter, the RLS clearly shows some advantages over the frequency domain technique for the present study. The significant advantages are:

(i) RLS is computationally simpler and faster as can be seen from Table 4. The computation time is evaluated for the 10 s simulation run, using the *'tic'* and *'toc'* commands of MATLAB. This time can vary with computer configuration.

Table 4. Computation time comparison

DFT	RLS
1.9650 s	0.2080 s

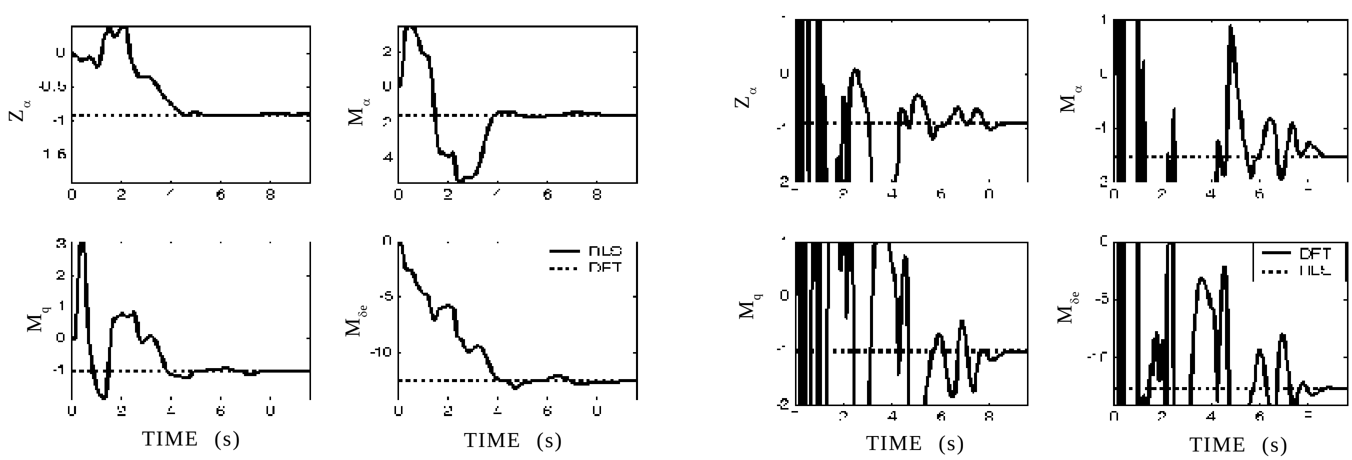

Figure 10. Convergence of estimates (real data).

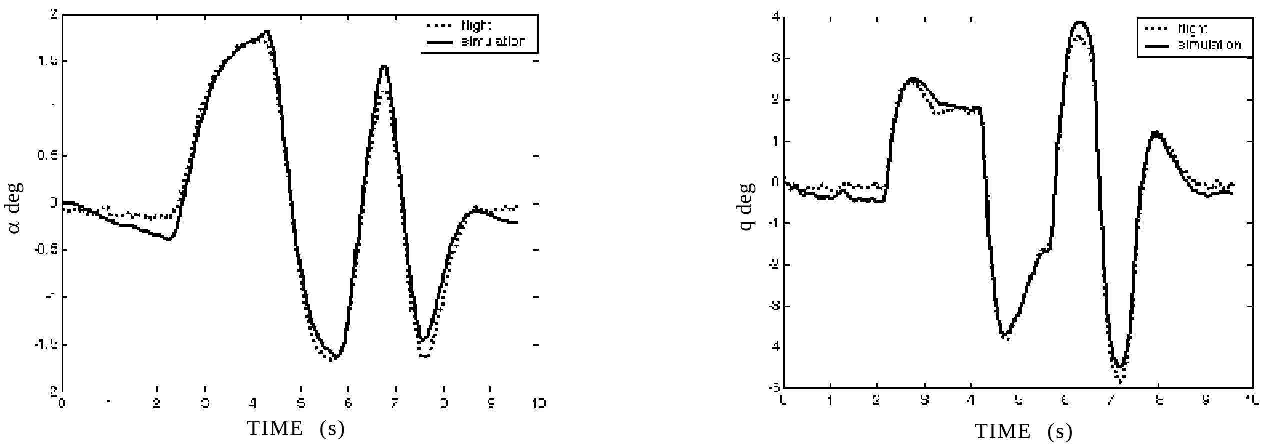

Figure 11. Comparison of estimated time histories with flight time histories (RLS).

The present work was carried out on a computer with the following specifications: Pentium (R) 4 CPU, 3.00 GHz, 1.00 GB of RAM. If *P* x *Q* is the size of the parameter matrix to be estimated then *Q* represents the order of the system. The computational complexity of algorithms can be shown in terms of *Q* considering only the number of multiplications and divisions involved per cycle. The number of discrete frequency points in DFT technique is denoted by *m* as discussed in Section 2.5. For the present study *m* is taken as 50. Table 5 shows the comparison of computational complexity between DFT and RLS wrt number of multiplications and divisions involved per cycle. A graph showing the growth of multiplications and divisions per cycle wrt the order of the system is shown in Fig. 12.

(ii) In RLS the correlation matrix inversion is replaced by scalar reciprocal. This is a considerable advantage in providing computational simplicity and would prevent numerical ill conditioning.

(iii) The convergence of estimates is less oscillatory during the initial phase of estimation. This is a desirable feature for adaptive control.

(iv) Since the time domain data is directly used and the estimate updates are achieved using the knowledge of Hessian, the convergence is faster.

(v) The usage of forgetting factor could enable the filter to operate in non-stationary environments also.

(vi) For the present study, the recursion starts with zero initial values, however, there is a provision to start with suitable initial values that will enable good convergence.

Table 5. Comparison of DFT with RLS-computational complexity

Floating point operation	Algorithm	Equation of floating point operation per cycle in terms of order of system ‘Q’	No. of operations 2^{nd}-order system
Multiplication	DFT	$m+4m(Q+1)+2Qm+4m(Q+1)^2+(Q+1)^2+(Q+1)^3+4m(Q+1)Q+(Q+1)^2Q$	3904
	RLS	$5(Q+1)+2(Q+1)^2+2(Q+1)Q+3Q$	51
Division	DFT	$(Q+1)^2$	9
	RLS	Q+1 (when λ = 1, for the present study λ is equal to1 because of stationary data) $(Q+1)+(Q+1)^2$(When λ is not equal to1, for non stationary data)	3

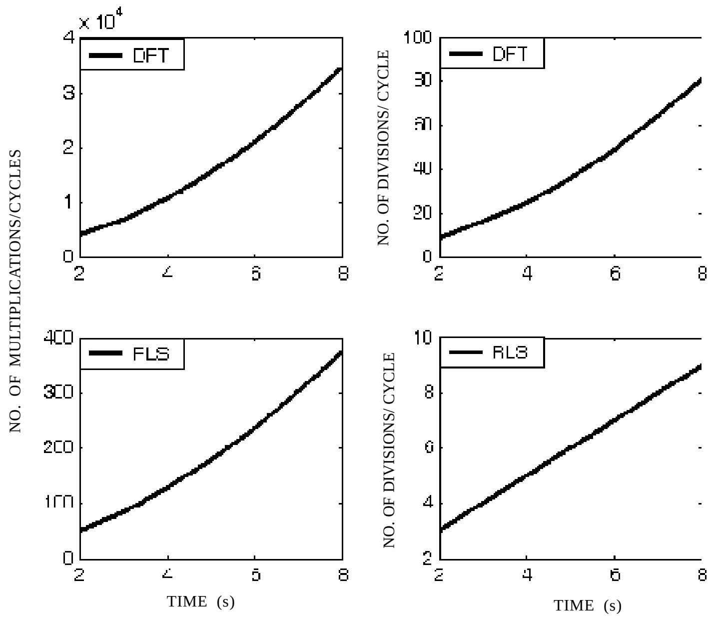

Figure 12. Comparison of RLS with DFT-floating point operations/cycle.

The disadvantage of the RLS technique could be the use of digital filters to remove the unwanted frequency bands. The digital filters produce time lags. However, this is avoided by identical filtering of all relevant signals. The advantage of DFT technique over RLS is that the data from previous flight maneuvers containing sufficiently good information for the identification purpose could still be utilised by iterating the calculation of DFT.

7. CONCLUSIONS

The parameter estimation of high performance unstable/augmented aircraft was implemented using two techniques: recursive DFT in frequency domain and RLS in time domain. Both the techniques achieved similar results showing their capability of estimating unstable/augmented aircraft parameters in the presence of correlated data. The algorithms were tested for their robustness considering noisy data with SNR 10. The results are satisfactory as can be confirmed from the Monte Carlo analysis. The convergence of estimates is faster in RLS and also the computation time is only about 1/10 of the time taken by DFT technique. This can be justified from Table 4 that shows the time consumed by DFT and RLS for 10 s simulation. In Table 5, the comparison of computational load involved in terms of multiplication and division operations for DFT and RLS could definitely support the above statement. Even though both the techniques are suitable for the parameter estimation of unstable/augmented aircraft, in the present study, most of the desirable features as required by an adaptive control, are met by the time domain RLS technique.

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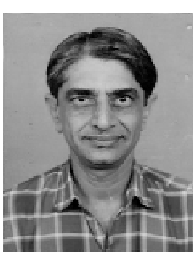

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