Attitude Dynamics Identification of Unmanned Aircraft Vehicle

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Abstract: The role of Unmanned Aircraft Vehicles (UAVs) has been increasing significantly in both military and civilian operations. Many complex systems, such as UAVs, are difficult to model accurately because they exhibit nonlinearity and show variations with time. Therefore, the control system must address the issues of uncertainty, nonlinearity, and complexity. Hence, identification of the mathematical model is an important process in controller design. In this paper, attitude dynamics identification of UAV is investigated. Using the flight data, nonlinear state space model for attitude dynamics of UAV is derived and verified. Real time simulation results show that the model dynamics match experimental data.

Keywords: Identification, nonlinear systems, UAV, state space models.

1. INTRODUCTION

UAVs have unmatched qualities that often make them the only effective solution in specialized tasks where risks to pilots are high, where beyond normal human endurance is required, or where human presence is not necessary. They have been used to perform missions in hazardous environments such as operations in nuclear power plants, exploration of Mars, and surveillance of enemy forces in the battlefield. Also, they are used for environmental monitoring, weather research, agricultural support, and mineral exploration. In general, the models for UAVs are dynamic with multiple inputs and outputs, and the measurements are noisy. While significant progress has been made in identification of linear systems over the broad spectrum of aerospace applications, the research to identify the nonlinear flight dynamics has been insufficient [1]. It has been recognized that the significant improvements of dynamic performance of current and new generation of advanced airplanes are possible if flight system design integrates nonlinear analysis, control, and identification [2]. Identification of nonlinear multi-input multi-output vehicles is a challenging problem and the current interest has been shifted to the issues of handling the nonlinear identification.

In this paper, a nonlinear mapping identification concept [2-6] is applied to identify the unknown parameters of attitude dynamics of UAV which is mapped by nonlinear differential equations. While nonlinear differential equations in a *generic* form can be found using Newtonian mechanics or the Lagrange equations of motion [7], the unknown parameters must be identified. The present work looks at the identification of the parameters that govern the attitude dynamics of UAV.

The test flights to collect the data were conducted at ADFA@UNSW, Australia.

The rest of the paper is organized as follows. Section 2 gives description of the identification approach. The attitude dynamics of UAV is presented in Section 3. Section 4 presents real time simulations using identification technique and in Section 5 some concluding remarks are presented.

2. STATE SPACE IDENTIFICATION

The nonlinear mapping identification method considers the system in the form

$$\dot{x}(t) = F(x,u),\ t \geq 0\ \ x(t_0) = x_0, \tag{1}$$

where $x \in R^c$ is the vector of the measured states with initial conditions $x(t_0) = x_0$, $u \in R^m$ is the known input vector, and $F(x,u)$ denotes a continuous vector function which is defined on $R^c \setminus \{0\}$ with $F(0,0) = 0$.

System (1) can be written in the matrix state space form as

$$\dot{x}(t) = A(t) f(x,u),\ t \geq 0,\ x(t_0) = x_0, \tag{2}$$

where $A(t) \in R^{cxn}$ is the real matrix, $f(x, u)$ denotes

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a given real analytic function, and $f(\bullet): R^c x R^m \to R^n$.

The identified state space model is defined as

$$\dot{x}_m(t) = A_m(t) f(x_m, u),\ t \ge 0,\ x_m(t_0) = x_{m0}. \tag{3}$$

Matrix coefficients, $A_m(t)$, are to be identified from flight data.

The normalized parameter error matrix $\Delta A(t) \in R^{cxn}$ is defined as

$$\Delta A(t) = A(t) - A_m(t). \tag{4}$$

The state error vector is introduced as

$$\begin{aligned} \Delta\dot{x}(t) &= \dot{x}(t) - \dot{x}_m(t) \\ &= \Delta A(t) f(x,u) + A_m(t)\Delta f(x, x_m, u), \\ t \ge 0&, \Delta x(t_0) = \Delta x_0. \end{aligned}$$

Here, $\Delta f(x, x_m, u) = f(x,u) - f(x_m, u)$.

The error vector is defined as

$$e(t) = \Delta\dot{x}(t) - A_m(t)\Delta f(x, x_m, u) = \Delta A(t) f(x,u). \tag{5}$$

An identification algorithm converges if

$$\lim_{t \to +\infty} \|e(t)\| = 0 \quad \text{and} \quad \lim_{t \to +\infty} \|\Delta A(t)\| = 0.$$

Using the differential equation for the normalized parameter error matrix as in [2-6], one has

$$\Delta\dot{A}(t) = -e(t) f(x,u)^T K, K \in R^{nxn}, \Delta A(t_0) = \Delta A_0, \tag{6}$$

where K is the weighting matrix. The selection of K affects the convergence of the identified parameters to their real values. It is chosen by the designer to guarantee the convergence and to attain the desired convergence rate.

From (5) and (6), one gets

$$\dot{A}_m(t) = \dot{A}(t) + e(t) f(x,u)^T K, A_m(t_0) = A_{m0}. \tag{7}$$

At a given flight condition, UAV dynamics can be assumed as time invariant, i.e., system parameters are constant. Hence system (2) becomes time invariant, so $\dot{A}(t) = 0$.

Then, we have the following nonlinear equation

$$\begin{aligned} &\dot{A}_m(t) = [\Delta\dot{x}(t) - A_m \Delta f(x, x_m, u)] f(x,u)^T K, \\ &A_m(t_0) = A_{m0}. \end{aligned} \tag{8}$$

The unknown parameters are found by solving nonlinear differential equation (8).

3. UAV ATTITUDE DYNAMICS

In this paper, the attitude dynamics of UAV is considered. The aircraft attitude dynamics is mapped by a set of three highly coupled nonlinear differential equations [7]. Instead of using an arbitrary structure these equations are used to get the basic structure for identification. The equations are

$$\begin{aligned} L &= \dot{p} I_x - \dot{r} I_{xz} + qr(I_z - I_y) - pq I_{xz}, \\ M &= \dot{q} I_y + pr(I_x - I_z) + (p^2 - r^2) I_{xz}, \\ N &= \dot{r} I_z - \dot{p} I_{xz} + pq(I_y - I_x) + qr I_{xz}, \end{aligned} \tag{9}$$

where L, M, and N are the rolling, pitching and yawing moments respectively, $p(t)$, $q(t)$, and $r(t)$ are the roll, pitch and yaw rates respectively, I_x, I_y, and I_z are the moment of inertia about x, y, and z respectively, and I_{xz} is the product moment of inertia. Simplifying (9), one gets

$$\begin{aligned} \dot{p} &= \frac{1}{I_x I_z - I_{xz}^2}\{I_z[L + (I_y - I_z)qr] + I_{xz}[N \\ &\quad + (I_x - I_y + I_z)pq - I_{xz} qr]\}, \\ \dot{q} &= \frac{1}{I_y}[M + pr(I_z - I_x) + (r^2 - p^2) I_{xz}], \\ \dot{r} &= \frac{1}{I_x I_z - I_{xz}^2}\{I_x[N + (I_x - I_y)pq] + I_{xz}[L \\ &\quad + (I_y - I_x - I_z)qr + I_{xz} pq]\}. \end{aligned} \tag{10}$$

Model the aerodynamic moments as

$$\begin{aligned} L &= L(p, r, \delta_a, \delta_r) = l_p p + l_r r + l_{\delta_a}\delta_a + l_{\delta_r}\delta_r, \\ M &= M(q, \delta_e, \delta_{th}) = m_q q + m_{\delta_e}\delta_e + m_{\delta_{th}}\delta_{th}, \\ N &= N(p, r, \delta_a, \delta_r) = n_p p + n_r r + n_{\delta_a}\delta_a + n_{\delta_r}\delta_r, \end{aligned} \tag{11}$$

where $\delta_e, \delta_r, \delta_a$, and δ_{th} are the elevator, ruder, aileron and throttle servos deflections respectively and l, m, and $n's$ are the aerodynamics derivative coefficients.

Substituting (11) into (10), one obtains

$$\begin{aligned} \dot{p} &= \frac{1}{I_x I_z - I_{xz}^2}\{I_z[[l_p p + l_r r + l_{\delta_a}\delta_a + l_{\delta_r}\delta_r] \\ &\quad + (I_y - I_z)qr] + I_{xz}[[n_p p + n_r r + n_{\delta_a}\delta_a \\ &\quad + n_{\delta_r}\delta_r] + (I_x - I_y + I_z)pq - I_{xz} qr]\}, \\ \dot{q} &= \frac{1}{I_y}[m_q q + + m_{\delta_e}\delta_e + m_{\delta_{th}}\delta_{th} + pr(I_z - I_x) \\ &\quad + (r^2 - p^2) I_{xz}], \\ \dot{r} &= \frac{1}{I_x I_z - I_{xz}^2}\{I_x[[n_p p + n_r r + n_{\delta_a}\delta_a + n_{\delta_r}\delta_r] \end{aligned} \tag{12}$$

$$+(I_x - I_y)pq] + I_{xz}[[l_p p + l_r r + l_{\delta_a}\delta_a + l_{\delta_r}\delta_r] + (I_y - I_x - I_z)qr + I_{xz}pq]\}.$$

The state vector is given by

$$x(t) = [p \quad q \quad r]^T = [x_1 \quad x_2 \quad x_3]^T.$$

By choosing

$$f(x,u) = \left[pq \;\; qr \;\; pr \;\; p^2 \;\; r^2 \;\; p \;\; q \;\; r \;\; \delta_e \;\; \delta_r \;\; \delta_a \;\; \delta_{th} \right]^T$$
$$= \left[x_1x_2 \;\; x_2x_3 \;\; x_1x_3 \;\; x_1^2 \;\; x_3^2 \;\; x_1 \;\; x_2 \;\; x_3 \;\; u_1 \;\; u_2 \;\; u_3 \;\; u_4 \right]^T,$$

and rewriting (12) according to (2), one obtains

$$A(t) = \begin{bmatrix} A_{11} & A_{12} & 0 & 0 & 0 & A_{16} & 0 & A_{18} & 0 & A_{110} & A_{111} & 0 \\ 0 & 0 & A_{23} & A_{24} & A_{25} & 0 & A_{27} & 0 & A_{29} & 0 & 0 & A_{212} \\ A_{31} & A_{32} & 0 & 0 & 0 & A_{36} & 0 & A_{38} & 0 & A_{310} & A_{111} & 0 \end{bmatrix},$$

where

$$A_{11} = \frac{I_{xz}(I_x - I_y + I_z)}{I_xI_z - I_{xz}^2}, \quad A_{12} = \frac{I_z(I_y - I_z) - I_{xz}^2}{I_xI_z - I_{xz}^2},$$
$$A_{16} = \frac{I_z l_p + I_{xz} n_p}{I_xI_z - I_{xz}^2}, \quad A_{18} = \frac{I_z l_r + I_{xz} n_r}{I_xI_z - I_{xz}^2}$$
$$A_{110} = \frac{I_z l_{\delta_r} + I_{xz} n_{\delta_r}}{I_xI_z - I_{xz}^2}, \quad \mathrm{A}_{111} = \frac{I_z l_{\delta_a} + I_{xz} n_{\delta_a}}{I_xI_z - I_{xz}^2},$$
$$A_{23} = \frac{I_z - I_x}{I_y}, \quad A_{24} = \frac{-I_{xz}}{I_y}, \quad A_{25} = \frac{I_{xz}}{I_y}, A_{27} = \frac{m_q}{I_y},$$
$$A_{29} = \frac{m_{\delta_e}}{I_y}, \quad A_{212} = \frac{m_{\delta_{th}}}{I_y},$$
$$A_{31} = \frac{I_x(I_x - I_y) + I_{xz}^2}{I_xI_z - I_{xz}^2}, \quad A_{32} = \frac{I_{xz}(I_y - I_x - I_z)}{I_xI_z - I_{xz}^2},$$
$$A_{36} = \frac{I_x n_p + I_{xz} l_p}{I_xI_z - I_{xz}^2}, \quad A_{38} = \frac{I_x n_r + I_{xz} l_r}{I_xI_z - I_{xz}^2},$$
$$A_{310} = \frac{I_x n_{\delta_r} + I_{xz} l_{\delta_r}}{I_xI_z - I_{xz}^2}, \quad \text{and} \quad \mathrm{A}_{311} = \frac{I_x n_{\delta_a} + I_{xz} l_{\delta_a}}{I_xI_z - I_{xz}^2}.$$

The matrix coefficients A are unknown and need to be identified.

The model identifier equation (3) is given by

$$\dot{x}_{m1} = A_{m11}x_{m1}x_{m2} + A_{m12}x_{m2}x_{m3} + A_{m16}x_{m1} + A_{m18}x_{m3} + A_{m110}u_2 + A_{m111}u_3,$$
$$\dot{x}_{m2} = A_{m23}x_{m2}x_{m3} + A_{m24}x^2{}_{m1} + A_{m25}x^2{}_{m3} + A_{m27}x_{m2} + A_{m29}u_1 + A_{m212}u_4,$$
$$\dot{x}_{m3} = A_{m31}x_{m1}x_{m3} + A_{m32}x_{m2}x_{m3} + A_{m36}x_{m1} + A_{m38}x_{m3} + A_{m310}u_2 + A_{m311}u_3.$$

Equation (5) leads to

$$\begin{aligned} e_1(t) &= \Delta\dot{x}_1 - [A_{m11}(x_{m1}x_{m3} - x_1x_3) + A_{m12}(x_{m2}x_{m3} - x_2x_3) + A_{m16}(x_{m1} - x_1) + A_{m18}(x_{m3} - x_3)], \\ e_2(t) &= \Delta\dot{x}_2 - [A_{m23}(x_{m1}x_{m3} - x_1x_3) + A_{m24}(x^2{}_{m1} - x^2{}_1) + A_{m25}(x^2{}_{m3} - x^2{}_3) + A_{m27}(x_{m2} - x_2)], \\ e_3(t) &= \Delta\dot{x}_3 - [A_{m31}(x_{m1}x_{m3} - x_1x_3) + A_{m32}(x_{m2}x_{m3} - x_2x_3) + A_{m36}(x_{m1} - x_1) + A_{m38}(x_{m3} - x_3)]. \end{aligned} \tag{13}$$

Using (7), (8), and (13), one gets

$$\dot{A}_m(t) = ef(x,u)^T K = [e_1(t) \quad e_2(t) \quad e_3(t)]^T$$
$$\left[x_1x_2 \;\; x_2x_3 \;\; x_1x_3 \;\; x_1^2 \;\; x_3^2 \;\; x_1 \;\; x_2 \;\; x_3 \;\; \delta_e \;\; \delta_a \;\; \delta_r \;\; \delta_{th} \right] K$$

If we assume that K is a diagonal matrix then

$$\begin{aligned} &\frac{dA_{m11}}{dt} = e_1(t)x_1(t)x_2(t)k_{11}, \ \frac{dA_{m12}}{dt} = e_1(t)x_2(t)x_3(t)k_{22}, \\ &\frac{dA_{m16}}{dt} = e_1(t)x_1(t)k_{66}, \ \frac{dA_{m18}}{dt} = e_1(t)x_3(t)k_{88}, \\ &\frac{dA_{m110}}{dt} = e_1(t)u_2(t)k_{1010}, \ \frac{dA_{m111}}{dt} = e_1(t)u_3(t)k_{1111}, \\ &\frac{dA_{m23}}{dt} = e_2(t)x_2(t)x_3(t)k_{33}, \ \frac{dA_{m24}}{dt} = e_2(t)x_1^2(t)k_{44}, \\ &\frac{dA_{m25}}{dt} = e_2(t)x_3^2(t)k_{55}, \ \frac{dA_{m27}}{dt} = e_2(t)x_2(t)k_{77}, \\ &\frac{dA_{m29}}{dt} = e_2(t)u_1(t)k_{99}, \ \frac{dA_{m212}}{dt} = e_2(t)u_4(t)k_{1212}, \\ &\frac{dA_{m31}}{dt} = e_3(t)x_1(t)x_2(t)k_{11}, \ \frac{dA_{m32}}{dt} = e_3(t)x_2(t)x_3(t)k_{22}, \\ &\frac{dA_{m36}}{dt} = e_3(t)x_1(t)k_{66}, \ \frac{dA_{m38}}{dt} = e_3(t)x_3(t)k_{88}, \\ &\frac{dA_{m310}}{dt} = e_3(t)u_2(t)k_{1010}, \text{ and } \frac{dA_{m311}}{dt} = e_3(t)u_3(t)k_{1111}. \end{aligned} \tag{14}$$

By solving nonlinear equation (14) the unknown parameters matrix can be identified.

The weighting matrix K is chosen so that the convergence of the identified parameters to the actual values is very fast. For the present work, it was selected as

$$K = diag\ [k_{ij}] \in R^{12x12}, \quad \text{where} \quad k_{ij} = 0.001.$$

The selection of a diagonal matrix makes it computationally easy to assess the effect of the

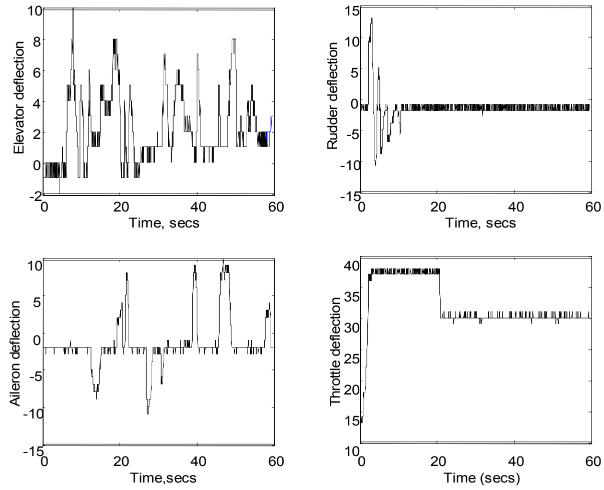

Fig. 1. Servos input data.

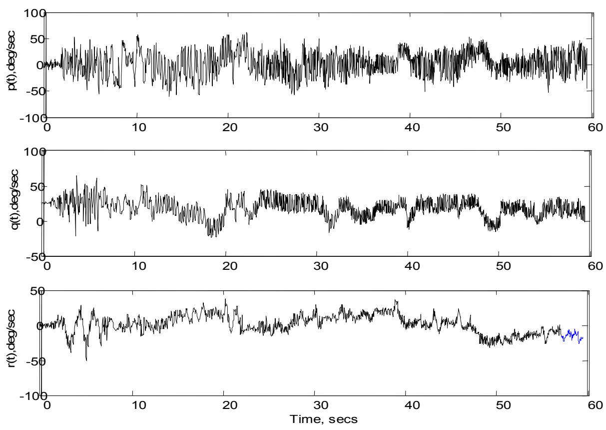

Fig. 2. Gyros output data.

elements in the K matrix for convergence. Also to check for the practicality of the K matrix, it was used at different flight conditions and the parameters conversion to the real values was achieved. However, the results for a particular flight condition only presented in this paper.

Flight tests were carried out to collect a range of data for differing flight conditions. Inertial Navigation Unit with three axis gyros and accelerometers is employed. Figs. 1 and 2 show the test flight data for a typical condition. Since the purpose of the present work is to demonstrate the capability for imitating the non-linear dynamics of UAV and not the dynamics characteristics of the UAV in terms of frequency and damping ratios of different modes of motions (short period, phugoid, etc.), no particular maneuver inputs were considered.

As shown in the Figs. 1 and 2 the data is noisy. This is due to the mounting of the Inertial Navigation Unit near the engine which imparts substantial noise to the platform and hence gyros. In addition, the gyros are cheap ones to minimise the cost of the unit and their sensitivity is 12.5mv/deg/sec.

4. RESULTS

The flight data are used directly for the identification. Before implementing the identification technique using on-board micro-controllers, and to check for the applicability of the identification techniques there is a necessity for real time simulation using Matlab/Simulink. Fig. 3 shows the real time simulation loop for the system where the flight data collected are taken at a sampling rate of 0.05. The identification algorithm is written as s-function. The simulink model is built and executed in real time.

Fig. 4 shows the identified model (grey) and the flight data (black). It is clear from Fig. 4 that the pitching rate, $q(t)$, is reasonably identified but for the roll rate, $p(t)$, and yaw rate, $r(t)$, the identified model and the actual values didn't match each other.

To improve this, the rolling and yawing moments are modeled as,

$$\begin{aligned} L &= L(p,r,\delta_a,\delta_r,\delta_{th}) = C_{l_p} p + C_{l_r} r + C_{l_{\delta_a}} \delta_a \\ &\qquad + C_{l_{\delta_r}} \delta_r + C_{l\delta_{th}} \delta_{th}, \\ N &= N(p,r,\delta_a,\delta_r,\delta_{th}) = C_{n_p} p + C_{n_r} r + C_{n_{\delta_a}} \delta_a \\ &\qquad + C_{n_{\delta_r}} \delta_r + C_{n\delta_{th}} \delta_{th}. \end{aligned} \tag{15}$$

This means two A coefficients are added to the

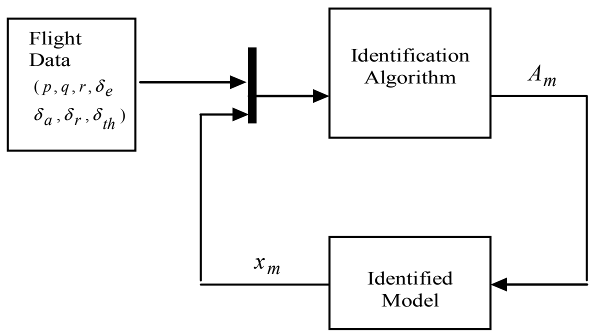

Fig. 3. Real time Simulation for UAV.

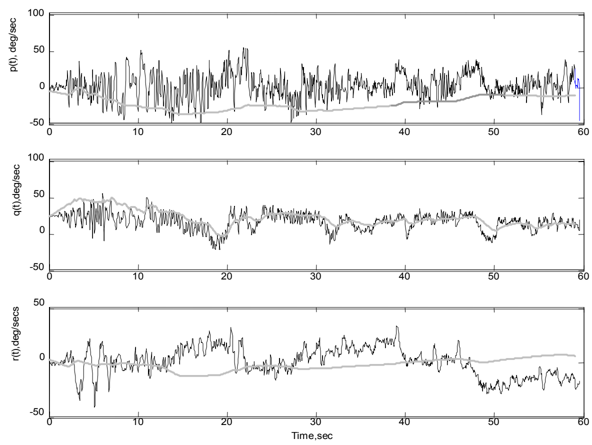

Fig. 4. Identified model (grey) and flight data (black).

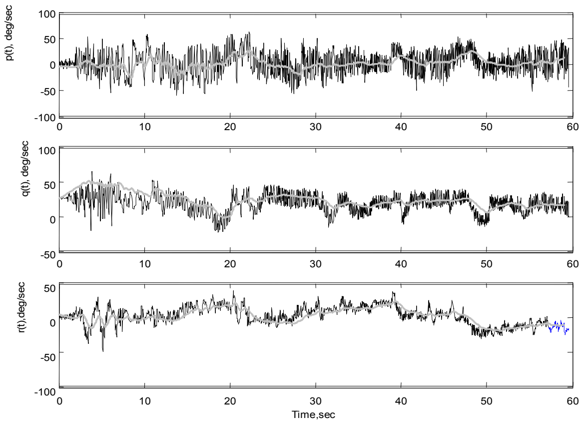

Fig. 5. Identified model (grey) and flight data (black).

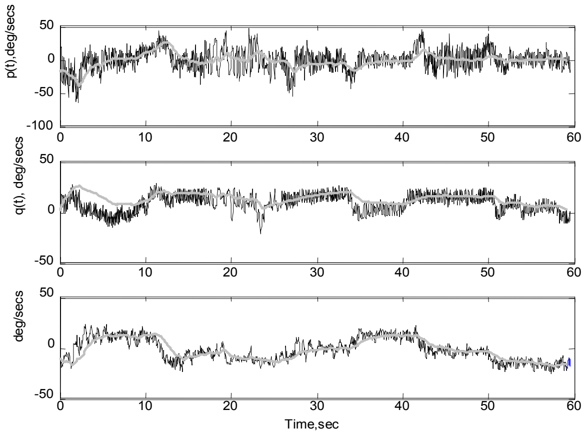

Fig. 6. Identified model (grey) and flight data (black).

structure as well as for the identifier model structure.

$$A_{112} = \frac{I_z l_{\delta_{th}} + I_{xz} n \delta_{th}}{I_x I_z - I_{xz}^2} \quad \text{and} \quad A_{311} = \frac{I_x n_{\delta_{th}} + I_{xz} l_{\delta_{th}}}{I_x I_z - I_{xz}^2}$$

After adding the two coefficients to UAV model we found that the identified model and the actual values matched for $p(t)$, $q(t)$, and $r(t)$ better than if we didn't include the throttle affect on rolling and yawing moments as shown in Fig. 5. Since our UAV is fixed wing UAV and is driven by a propeller, the change in the modelling of the rolling and pitching moments is reasonably accurate and that is clearly recognized from the results. Fig. 6 shows comparison of results for another set of flight data for which the identified model has been tried.

The numerical values for the parameters of the A matrix are given by

$A_{11} = 0.0010$, $A_{12} = 0.0107$, $A_{16} = -0.1361$, $A_{18} = 0.0111$, $A_{110} = 0.0181$, $A_{111} = 0.0030$, $A_{112} = 0.0014$, $A_{23} = 0.0107$, $A_{24} = -0.0103$, $A_{25} = 0.0103$, $A_{27} = -0.1090$, $A_{29} = 0.0105$, $A_{212} = 0.0004$, $A_{31} = 0.0102$, $A_{32} = 0.0093$, $A_{36} = 0.0104$, $A_{38} = -0.1032$, $A_{310} = -0.0011$, $A_{311} = 0.0054$, and $A_{312} = 0.0001$.

5. CONCLUSIONS

The main contribution of this paper is the solution of the nonlinear identification problem for UAV attitude dynamics which are described by nonlinear differential equations. Also, changing in the modeling of the rolling and yaw moment to include the effect of the throttle is reasonably accurate for fixed wing UAV which is driven by a propeller. A nonlinear mapping identification concept is applied to identify the unknown parameters of multivariable UAV which is mapped by nonlinear differential equations. Real time simulation results show good match between the flight data and the simulated data after including the effect of throttle on the rolling and yawing moments. Presently the work is continuing to reduce the gyro noise, the Hardware-In-Loop simulation and the verification for on-line identification. In addition the design of a suitable controller based on the identified model is currently under development.

REFERENCES

[1] E. A. Morelli, "System identification programs for aircraft (SIDPAC)," *Proc. of AIAA Atmospheric Flight Mechanics Conference*, Monterey, Aug. 5-8 2002.

[2] S. E. Lyshevski, "State-space identification of nonlinear flight dynamics," *Proc. of the IEEE International Conference on Control Applications*, Hartford, CT, pp. 496-498, October 5-7, 1997.

[3] S. E. Lyshevski and Y. Chen, "Nonlinear identification of aircraft," *Proc. of IEEE International Conference on Control Applications*, Dearborn, MI, pp. 327-331, September 15-18, 1996.

[4] S. E. Lyshevski, "Identification of nonlinear flight dynamics: Theory and practice," *IEEE Trans. on Aerospace and Electronic Systems*, vol. 36, no. 2, pp. 383-392, April, 2000.

[5] S. E. Lyshevski, "Identification of nonlinear systems with noisy data: A nonlinear mapping-based concept in time domain," *Proc. of American Control Conference*, vol. 2, pp. 1634-1635, June 25-27, 2001

[6] V. Pappano, S. E. Lyshevski, and B. Friedland, "Nonlinear identification of induction motor parameters," *Proc. of the American Control Conference*, vol. 5, pp. 3569-3573, June 1999.

[7] J. Roskam, *Airplane Flight Dynamics and Automatic Flight Controls*, DAR corporation, Lawrence, Kan, 1995.

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