ON-LINE IDENTIFICATION AND NONLINEAR CONTROL OF ROTORCRAFT/EXTERNAL-LOAD SYSTEMS

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Abstract

There has been recent interest in improving helicopter flying qualities when the vehicle is carrying an external-load. This is widely regarded as a difficult operating condition, and will likely require an advanced control method. We propose here a model predictive control approach, which requires accurate models of the coupled rotorcraft/load dynamic system. However, such models typically do not exist, and on-line model identification will be required to obtain them. The challenge here is to represent the load's effects in a manner that is measurable. This was overcome by representing the load dynamics in terms of the forces and moments imparted to the helicopter by the tension in the cable that carries the load. The Modified Sequential Least Squares approach was used to identify the load dynamics represented in this fashion. The need for identifying load dynamics was shown to be evident. The highly coupled nature of the rotorcraft/load dynamic system requires inclusion of an identified load model for accurate predictions of the system responses. Simulation results of the identified system showed good one to two second predictions of the dynamics. This should be an adequate prediction window for a successful feedback control design. A preliminary model-predictive control approach is also presented and shows promising results.

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Introduction

The work presented in this paper was motivated by the Helicopter Active Control Technology (HACT) Phase I program funded by the U.S. Army's Aviation Applied Technology Directorate and the Aeroflightdynamics Directorate. The overall HACT objectives are to investigate potential benefits of using modern, multivariable active control methodologies for difficult helicopter control scenarios. The focus of this study is to investigate control issues relevant to a helicopter with an external-load. Pilot workload can increase significantly under this particularly difficult flight regime. Under emergency situations such as disaster relief, fire fighting, or supplying cargo to combat troops, the pilot must acquire and deliver the load rapidly while also concentrating on difficult flight, guidance and navigation objectives. A control system able to actively aide the pilot in stabilizing the helicopter/external-load system could reduce his workload and greatly enhance the overall system performance. With better maneuverability the pilot can deliver the needed cargo safer and faster. Furthermore, active control may increase the load carrying capabilities, enabling the pilot to deliver a broader range of different types of loads that would otherwise be prohibitive due to original system limitations.

In the course of the current study, we identified two main challenges in the control of helicopter and external-load systems. These challenges are as follows:

1. Under adverse emergency scenarios, the load dynamics, weight, and cable length may be unknown. Therefore, models of load dynamics are unavailable in control design. Placing sensors on the load to measure its position, rates and/or

accelerations is usually impractical. Therefore, load states are not directly measurable.

2. *Intelligent* control of the helicopter/external-load system takes on new behaviors not seen in traditional control approaches. A traditional control scheme treats the influence of the external-load as a disturbance to the rotorcraft.[1-4] This control methodology seems to be the obvious choice given that the load dynamics and states are unknown. However, as illustrated in Fig. 1, this approach is counterintuitive to the control of pendulum motion. As the load swings aft, the control law will command the rotorcraft to pitch over and fly forward to "reject" the disturbance, or rearward forces imparted to the helicopter from the load. This then causes a larger swing forward, and instability might eventually result. Fig. 2 illustrates a more intelligent control method. Here, the control law commands the helicopter to maneuver with the load's motion, providing increased damping to the system. The resulting swinging of the load is then stabilized.

Some information regarding the load is almost certainly a requirement for a successful modern intelligent control design. The entire rotorcraft/load motion must be accurately predicted to provide the proper feedback control signals. This can be done only with the use of a dynamic model of the load. However, as just discussed, such an *a-priori* load model will not exist, especially if the mission often calls for rapid acquisition and delivery of many different types of cargo. It is therefore of paramount interest to develop techniques for identifying the load dynamics on-line for use in active control of the external-load.

During the summer of 1996, a series of flight tests demonstrated an adaptive approach to reconfigurable flight control termed the self-designing flight controller (SDC). This indirect adaptive control architecture computed a time-varying model of the complete aircraft dynamics (stability and control derivatives), and an on-board optimal controller calculated effector commands to achieve the desired aircraft responses based on the identified dynamics. Using residual control authority, the system was shown to reconfigure rapidly to single and multiple *de-stabilizing* impairments. The class of failures considered was missing control surfaces resulting in a reduction of aircraft stability and decreased effectiveness. The key enabling technology was a novel on-line system identification technique (known as Modified Sequential Least Squares, or MSLS) that could rapidly track time-varying parameters and that was robust to adverse conditions of low-excitation and correlated inputs. We feel that this algorithm is the ideal approach to the current identification problem.

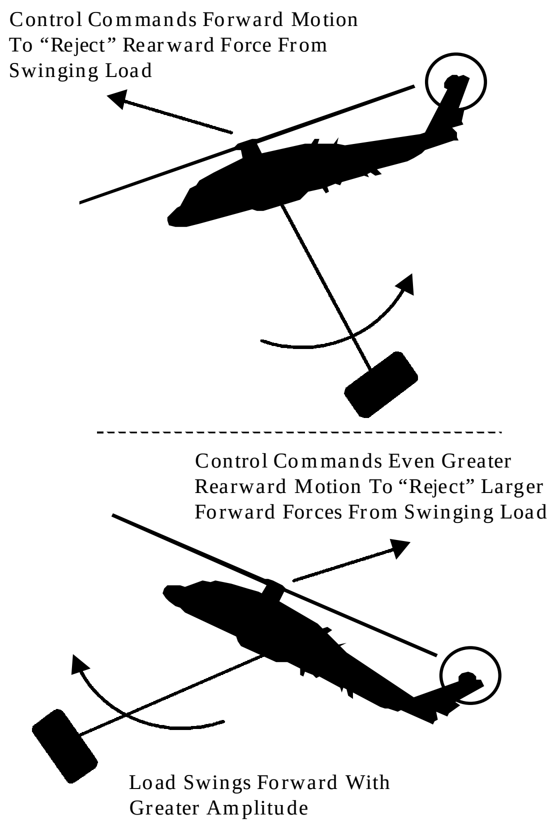

Fig. 1. "Disturbance Rejection" Approach – Load Model Not Required

A description of the system used in this study will first be summarized. The identification methodology and results will then be presented. A preliminary control study is then discussed, followed by conclusions.

System Description

A Linear Time-Invariant (LTI) state-space model of a Sikorsky UH-60L rotorcraft in hover was used in this study. The load considered in this model is a HUMVEE truck. It is carried by four cables, with two attached to the front bumper of the truck and two attached to its rear bumper. The four cables are all attached to the UH-60L cargo hook located underneath the fuselage. The hook is located 3.9 inches in front of the c.g. and 52.2 inches below the c.g.

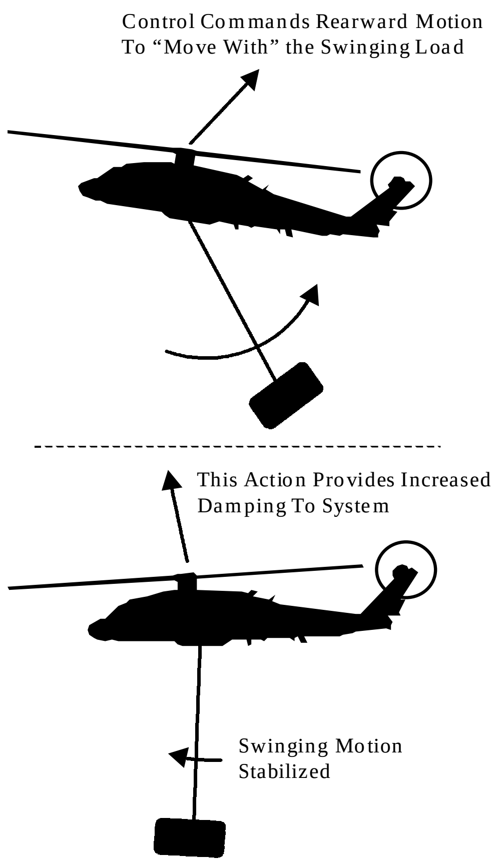

Fig. 2. "Intelligent Control" Approach – Load Dynamic Model Required

The "Truth" Model

The "truth" model is a 34th order linear time invariant state space model derived from a high fidelity nonlinear model. The model was supplied by Sikorsky Aircraft Corp, and includes the usual rigid-body rotorcraft translational and rotational states: {u, v, w, p, q, r, ϕ, θ, ψ}. In a like manner, the model includes nine load rigid-body states, defined with respect to its own body-fixed axis, and position states defining the load c.g. position relative to the rotorcraft's c.g. position. The model also includes states describing the rotor flapping, lagging and inflow dynamics The initial conditions are steady-state hover with no load motion.

The available controls are longitudinal and lateral cyclic pitch, main and tail rotor collective, and stabilator incidence angle. It was assumed that measurements available for feedback and identification algorithms are all rotorcraft rigid body states, and translational and rotational accelerations. That is, $\{u, v, w, p, q, r, \phi, \theta, \psi, \dot{u}, \dot{v}, \dot{w}, \dot{p}, \dot{q}, \dot{r}\}$. It is assumed that these quantities are either directly measured or are generated via, for example, a Kalman filter using physical measurements. Note that no load states are available.

The linear 34th order "truth" model is denoted and partitioned as:

$$\dot{x} = Ax + Bu$$
$$y = Cx + Du$$
$$\begin{Bmatrix} \dot{X}_H \\ \dot{x}_L \end{Bmatrix} = \begin{bmatrix} \overline{A}_H & \overline{A}_{LH} \\ \overline{A}_{HL} & A_L \end{bmatrix} \begin{Bmatrix} X_H \\ x_L \end{Bmatrix} + \begin{bmatrix} \overline{B}_H \\ B_L \end{bmatrix} u \tag{1}$$
$$y = \begin{bmatrix} C_H & 0 \end{bmatrix} \begin{Bmatrix} X_H \\ x_L \end{Bmatrix} + D_H u$$

where the subscript "H" denotes helicopter states and the subscript "L" denotes load states. The matrices $\overline{A}_{HL}$ and $\overline{A}_{LH}$ reflect the coupled dynamics between the rotorcraft and the load it is carrying. The subscripts "LH" and "HL" denote load-to-helicopter and helicopter-to-load, respectively. The overbar notation and uppercase X in X_H are used because the helicopter system will be further partitioned later. The matrix B_L is taken to be zero. That is, the helicopter control effectors do not directly control the load.

In almost all of the studies performed, only the lateral and longitudinal cyclic pitch input channels were considered. Furthermore, these studies used three primary types of control inputs: the doublet, the sine wave and the chirp signal, (a sine wave with continually increasing frequency). Focusing on the two input channels and the three particular types of input signals was done for proof-of-concept studies. More extensive investigations will require us to address all input channels and a larger array of inputs. Finally, "truth" model responses were generated for the system excited by the control inputs considered. The simulation was performed using the *MATLAB/Simulink* software package.

Models Used in the ID Process

Model reductions, modeling errors, and measurement noise were added to the system to simulate real-world effects of unmodeled and/or uncertain dynamics and sensor inaccuracies. Measurements were generated by adding zero-mean white Gaussian noise to the simulated "truth" responses. The 1-σ values for each measurement were taken to be 1-5% of their respective maximum values. The identification and estimation methods discussed here require knowledge of the control input signals. *Measurements of the control signals* were generated in a like manner by adding noise to their "truth" values.

Since rotor states are not available as measurements, we decided to eliminate them from the model. Although use of a residualization technique to eliminate rotor states would provide a more accurate lower order model, we instead *truncated* the rotor states from the model to simulate additional modeling errors. Further parameter errors were generated by adding normally distributed random numbers to each of the parameters in the model, with 1-σ values = 5% of each respective nominal parameter magnitude. For proof-of-concept studies, we feel that these model reductions and parameter variations approximate errors sources that would be typically encountered. The reduced order models with parameter errors will be denoted with a "~" as:

$$\begin{Bmatrix} \dot{X}_H \\ \dot{x}_L \end{Bmatrix} = \begin{bmatrix} \tilde{\bar{A}}_H & \tilde{\bar{A}}_{LH} \\ \tilde{\bar{A}}_{HL} & \tilde{A}_L \end{bmatrix} \begin{Bmatrix} X_H \\ x_L \end{Bmatrix} + \begin{bmatrix} \tilde{\bar{B}}_H \\ \tilde{B}_L \end{bmatrix} u \tag{2}$$

Identification Methodology

The identification process requires measurements of the inputs and outputs to the system. However, measurements of the load states are unavailable. Therefore, we decided to redefine the system description of the load to take direct advantage of the observable load information. The system of Eq. (1) can be further partitioned as follows:

$$\begin{Bmatrix} \dot{x}_H \\ \dot{x}_K \\ \dot{x}_R \\ \dot{x}_L \end{Bmatrix} = \begin{bmatrix} A_H & A_{KH} & A_{RH} & A_{LH} \\ A_{HK} & A_K & A_{RK} & A_{LK} \\ A_{HR} & A_{KR} & A_R & A_{LR} \\ A_{HL} & A_{KL} & A_{RL} & A_L \end{bmatrix} \begin{Bmatrix} x_H \\ x_K \\ x_R \\ x_L \end{Bmatrix} + \begin{bmatrix} B_H \\ B_K \\ B_R \\ B_L \end{bmatrix} u \tag{3}$$

where,

x_H = helicopter rigid body dynamic states
= $\{u, v, w, p, q, r\}^T$

x_K = helicopter kinematic states = $\{\theta, \phi, \psi\}^T$

x_R = rotor states

x_L = load states
= $\{u_L, v_L, w_L, p_L, q_L, r_L, \theta_L, \phi_L, \psi_L, n_{rel}, e_{rel}, z_{rel}\}^T$

Note that the load states do not affect the helicopter kinematic states; hence, $A_{LK} = 0$. From the first partitioned row in Eq. (3), we define the following vector

$$z = A_{LH} x_L = \dot{x}_H - A_H x_H - A_{KH} x_K - A_{RH} x_R - B_H u \tag{4}$$

Here, z is a 6x1 vector and represents the most direct observation of the load's effect on the helicopter's rigid-body motion. Physically, the elements in this vector are the forces and moments imparted to the rotorcraft from the tension in the cable that carries the load - normalized by the mass of the rotorcraft and its mass-moments of inertia. The measurements represent the forces and moments resolved into the helicopter's body axis coordinates. Table 1 gives the specific definition of each measurement. In Table 1, m is the mass of the helicopter, and I_{xx}, I_{yy} and I_{zz} are the mass moments of inertia about the helicopter's body x, y and z axes, respectively. Fig. 3 illustrates the forces generated by the cable tension and the moment arms from the c.g. to the cargo attach point. Note that the location of the c.g. is exaggerated for clarity. From Fig. 3 it can be seen that the moments are:

$$\begin{aligned} m_x &= \tau_z d_y - \tau_y d_z \\ m_y &= \tau_x d_z - \tau_z d_x \\ m_z &= -\tau_x d_y + \tau_y d_x \end{aligned} \tag{5}$$

We also noted that the load's swinging motion will be stabilized if the rates of changes of the forces $\{\tau_x, \tau_y, \tau_z\}$ *and the rotorcraft's attitude motion are simultaneously driven to zero* (see Fig. 2). That is, these force rates are zero if the load is at rest with respect to the rotorcraft. Hence, it is the forces imparted to the rotorcraft from the load that are of primary importance in the control problem. The load states, as defined in the original "truth" model are really not of interest since they cannot even be directly measured. Therefore, the key to our approach is to use the z-vector of Eq. (4) as the states of a redefined "load" dynamic model. Note that this description reduces the order of the load model from twelve to six. The reason for this is that we are now modeling the effect of the load on the helicopter. We are no longer concerned with the load's position and attitude dynamics, which require a twelve state model.

Table 1. Physical Definition of Measurement Vector, z

z-vector	Definition
1. $z_1 = \frac{\tau_x}{m}$	τ_x = body-x force imparted to vehicle from tension in load cable
2. $z_2 = \frac{\tau_y}{m}$	τ_y = body-y force imparted to vehicle from tension in load cable
3. $z_3 = \frac{\tau_z}{m}$	τ_z = body-z force imparted to vehicle from tension in load cable
4. $z_4 = \frac{\omega_x}{I_{xx}}$	ω_x = moment about body-x axis generated from cable tension
5. $z_5 = \frac{\omega_y}{I_{yy}}$	ω_y = moment about body-y axis generated from cable tension
6. $z_6 = \frac{\omega_z}{I_{zz}}$	ω_z = moment about body-z axis generated from cable tension

Using the z states, the system can be written as

$$\begin{Bmatrix} \dot{x}_H \\ \dot{x}_K \\ \dot{x}_R \\ \dot{z} \end{Bmatrix} = \begin{bmatrix} A_H & A_{KH} & A_{RH} & I \\ A_{HK} & A_K & A_{RK} & 0 \\ A_{HR} & A_{KR} & A_R & A_{ZR} \\ A_{HZ} & A_{KZ} & A_{RZ} & A_Z \end{bmatrix} \begin{Bmatrix} x_H \\ x_K \\ x_R \\ z \end{Bmatrix} + \begin{bmatrix} B_H \\ B_K \\ B_R \\ B_Z \end{bmatrix} u \quad (6)$$

Description of Case Studies

A baseline identification study was performed in which all states in Eq. (4) were available to form the measurements. Also, no noise or parameter errors were introduced. In this case, the identification process will generate numerical values for the elements in the matrices A_{ZR}, A_{HZ}, A_{KZ}, A_{RZ}, A_Z, and B_Z in Eq. (6).

Because rotor state measurements are not typically available, we next performed the identification with these states truncated out. This reduced state model is:

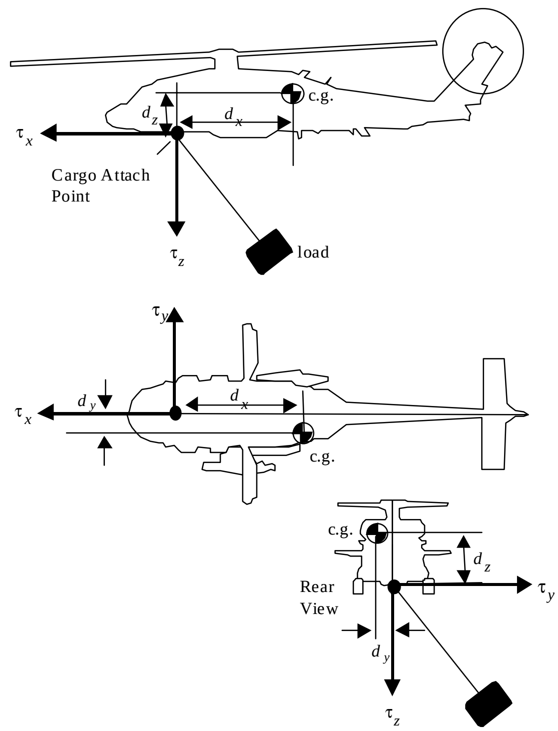

Figure 3. Forces Imparted To Rotorcraft From Cable Tension.

$$\begin{Bmatrix} \dot{x}_H \\ \dot{x}_K \\ \dot{z} \end{Bmatrix} = \begin{bmatrix} A_H & A_{KH} & I \\ A_{HK} & A_K & 0 \\ A_{HZ} & A_{KZ} & A_Z \end{bmatrix} \begin{Bmatrix} x_H \\ x_K \\ z \end{Bmatrix} + \begin{bmatrix} B_H \\ B_K \\ B_Z \end{bmatrix} u \quad (7)$$

The corresponding equation for z is:

$$z = \dot{x}_H - A_H x_H - A_{KH} x_K - B_H u \quad (8)$$

For this second case, parameter errors were *not* included in any of the of matrices in Eqs. (7) and (8). Furthermore, z was generated using the "truth" simulation data. Here, the identification process will generate numerical values for the elements in the matrices A_{HZ}, A_{KZ}, A_Z, and B_Z.

Finally, measurement noise and parameter errors were introduced. From Eq. (3), the vector of available measurements can be written as:

$$y = \{x_{Hm} \quad x_{Km} \quad \dot{x}_{Hm}\}^T \quad (9)$$

where the subscript "m" indicates a measured quantity. In this case, the equation for z becomes:

$$z = \dot{x}_{Hm} - \tilde{A}_H x_{Hm} - \tilde{A}_{KH} x_{Km} - \tilde{B}_H u_m \qquad (10)$$

Again, recall that "~" denotes that parameter errors are included. Eq. (10) is currently the most realistic representation of the *measurement* vector z. Various filtering schemes of the z-measurements were investigated, including Kalman and low-pass filtering. For the results presented here, a low-pass filter was used, and the *best estimate* z-vector is defined by:

$$\hat{z} = \hat{\dot{x}}_H - \tilde{A}_H \hat{x}_H - \tilde{A}_{KH} \hat{x}_K - \tilde{B}_H \hat{u} \qquad (11)$$

where the "^" indicates a low-pass filtered quantity.

The three cases discussed above are summarized below.

Case 1. <u>Baseline – Full Order "Truth" Model With "Truth" Information Available</u>

State Model (Eq. (6))
Measurement Model (Eq. (4)):
Identified: A_{ZR}, A_{HZ}, A_{KZ}, A_{RZ}, A_Z, and B_Z

Case 2. <u>Reduced Order "Truth" Model With "Truth" Information Available (Rotor States Truncated)</u>

State Model (Eq. (7)):
Measurement Model (Eq. (8)):
Identified: A_{HZ}, A_{KZ}, A_Z, and B_Z

Case 3. <u>Reduced Order Model With Parameter Errors and Noisy Measurements</u>

State Model:

$$\begin{Bmatrix} \dot{x}_H \\ \dot{x}_K \\ \dot{z} \end{Bmatrix} = \begin{bmatrix} \tilde{A}_H & \tilde{A}_{KH} & I \\ \tilde{A}_{HK} & \tilde{A}_K & 0 \\ A_{HZ} & A_{KZ} & A_Z \end{bmatrix} \begin{Bmatrix} x_H \\ x_K \\ z \end{Bmatrix} + \begin{bmatrix} \tilde{B}_H \\ \tilde{B}_K \\ B_Z \end{bmatrix} u \qquad (12)$$

Measurement Model (Eq. (11):
Identified: A_{HZ}, A_{KZ}, A_Z, and B_Z

Identification Algorithm – (MSLS)

Again, we chose to use the Modified Sequential Least-Squares (MSLS) approach to perform the identification. This approach is summarized here, and more complete discussions are given in the references.[5,6] First, we discuss why MSLS is a viable approach for the current problem.

The task addressed here is the identification of coupled rotorcraft and external-load dynamics for a hover operating condition. The physical system is characterized by nonlinear, open-loop unstable dynamics which will pose considerable challenges for identification of rotorcraft and load dynamics, particularly when real-time operation under feedback control is required. As discussed previously, the efficacy of using MSLS to accurately identify slow and fast (near-instantaneous) parameter variations for on-line control was demonstrated via *actual flight tests*. This capability is one reason for applying the approach to the identification of coupled rotorcraft and load dynamics. Another advantage of MSLS is that the algorithm framework allows several types of parameter constraints to be included; in the context of the current task, one might include constraints that capture, at least at a high level, the physics of the coupled system.

In many cases, nonlinear system dynamics can be adequately represented by linear time-varying state equations in which the nonlinear behavior is represented by (possibly) different stability and control derivatives (A and B matrices, respectively) at each control update. This is the assumption here, where the "truth" model is a linear model of the helicopter at one flight condition. Although advantageous for control, this piecewise-linear approximation can result in rapid variations in the parameters that are to be identified. The presence of time-varying parameters translates into a need for rapid adaptation, and, therefore, a need for short memory length. However, this requirement contradicts the need of stretching the algorithm memory to obtain uncorrelated inputs to the identification process. The MSLS algorithm incorporates constraints to prevent numerical difficulties that can occur when data windows are small enough to track rapidly varying parameters. The constraints are added to a standard squared-error cost function with a forgetting factor to yield a total performance metric to be minimized:

$$J(\theta) = \frac{1}{2} \sum_{n=t_o}^{t} \{\lambda^{t-n} r(n)^T r(n)$$
$$+ q(n)^T W_o q(n) + p(n)^T W_1 p(n)\} \quad (13)$$

where,

$$r(n) = y(n) - \theta^T (n-1)\phi(n)$$
$$q(n) = \theta(n) - \theta(n-1) \quad (14)$$
$$p(n) = M\theta(n) - k$$

where y and ϕ are vectors of measured signals, θ is a matrix of estimated parameters, $0 < \lambda < 1$ is a forgetting factor used to discount prior observations. Here, W_o and W_1 are matrices of relative penalties associated with the constraints. The first set of constraints in the cost function (associated with the parameter $q(n)$) are known as *temporal* constraints, and penalize parameter values that deviate from their previous estimates. Temporal constraints result in a smoothing over time, but do not hinder the ability to track rapidly varying parameters given sufficient excitation. The second set of constraints (associated with the parameter $p(n)$) are known as spatial constraints, which penalize parameter estimates that differ from *a priori* estimates of the model parameters, or these might also include relationships among different parameters. For example, the lift and moment generated by a tail surface of a fixed-wing aircraft are related by the distance to the center of gravity, and this relationship may be incorporated as a spatial constraint. Other constraints based on flight dynamics have been used successfully. As alluded to previously, it might also be possible to define similar *generic* relationships for the coupled rotorcraft/external-load system which hold for all loads.

Because our current proof-of-concept study involves identification of a linear time-invariant system, the full capabilities of the MSLS algorithm were not required. Therefore, a simplified variant of the complete MSLS algorithm was used and found to be sufficient. However, the MSLS algorithm was developed for nonlinear, time-varying on-line identification, and we recommend using its full capabilities for later stages in the development of this approach.

Identification Results

Throughout this section, a representative set of rotorcraft state responses is presented. This included forward velocity (u ~ ft/sec), vertical velocity (w ~ ft/sec), roll rate (p ~ rad/sec), and pitch rate (q ~ rad/sec). The state responses that are not shown have similar characteristics.

The model was first simulated with no identification of the z states for both the full order helicopter model and the reduced order rigid-body helicopter model (rotor states truncated out). The truncated models are compared against the "truth" model in Fig. 4. Here, even the full order helicopter model does not compare well with the "truth" results, indicating the high degree of dynamic coupling between the rotorcraft and the load it is carrying. These results underscore the need for identifying the load dynamics and their effect on the rotorcraft motion.

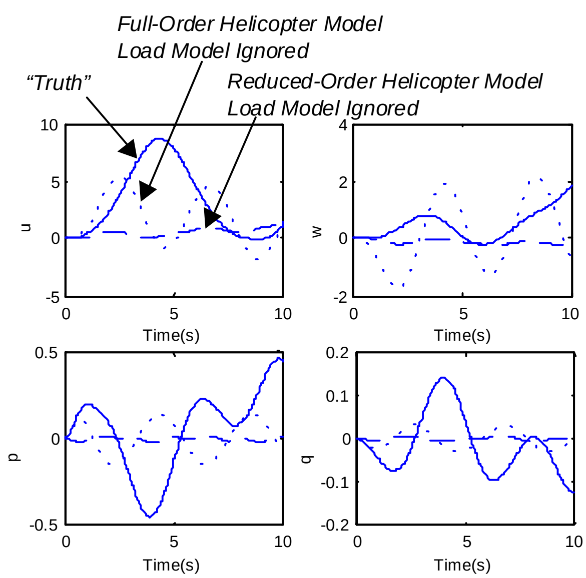

Figure 4. Simulations Ignoring Load Dynamics

Next, Case 1, or the Baseline Case was performed in which we assumed all helicopter rigid-body and rotor states were measurable and could be used in the identification process. Again, no noise or parameter errors were considered. Using the MSLS algorithm, the matrices A_{ZR}, A_{HZ}, A_{KZ}, A_{RZ}, A_Z, and B_Z in Eq. (6) were identified with sinusoidal excitations to the lateral and longitudinal cyclic input channels. Once these parameters were found, the system described by Eq. (6) was integrated forward using a variety of input functions. The results for sinusoidal inputs are shown in Fig. 5.

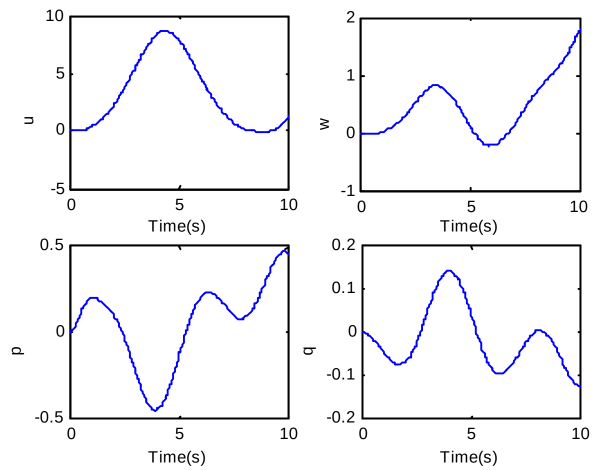

Figure 5. Case 1. Identification of Load Dynamic Model Using Full-Order Helicopter Model With No Parameter Errors or Measurement Noise

It is evident that the identification of load dynamics is highly accurate. The results shown in Fig. 5 indicate an almost exact match between the "truth" system and the identified system. Therefore, expressing the effects of the load's dynamic interaction with the rotorcraft in terms of the z-states (or, as described in Table 1) does not seem to degrade the model's accuracy. Recall that this model description has six fewer states than the "truth" model.

Next, Case 2 was performed in which we assume only the helicopter's rigid-body states and state rates are measurable (to be used in the identification process). Therefore, the rotor states are truncated out of the model. Again, no noise or parameter errors were considered. Using the MSLS algorithm, the matrices A_{HZ}, A_{KZ}, A_Z, and B_Z in Eq. (7) were identified with sinusoidal excitation inputs. Once these parameters were found, the system described by Eq. (7) was integrated forward with several different inputs. Simulation results of this system are shown in Fig. 6 for sinusoidal inputs.

It can be seen that for Case 2, the identification of the load system is excellent. The modeling errors introduced by truncating out the rotor states has minimal effect on the accuracy of the identified model.

More realistic effects are next introduced in Case 3. Here, not only do we use the truncated helicopter state model, as in Case 2, but we also add parameter errors and use the filtered z-measurements generated by Eq. (11). Using the MSLS algorithm, the matrices A_{HZ}, A_{KZ}, A_Z, and B_Z in Eq. (12) were identified with a sinusoidal excitation input. Once these parameters were found, the system described by Eq. (12) was simulated. The results for sinusoidal inputs are shown in Fig. 7. For a reference, the rigid-body helicopter model alone (i.e. no load dynamics included) was also simulated with model uncertainty.

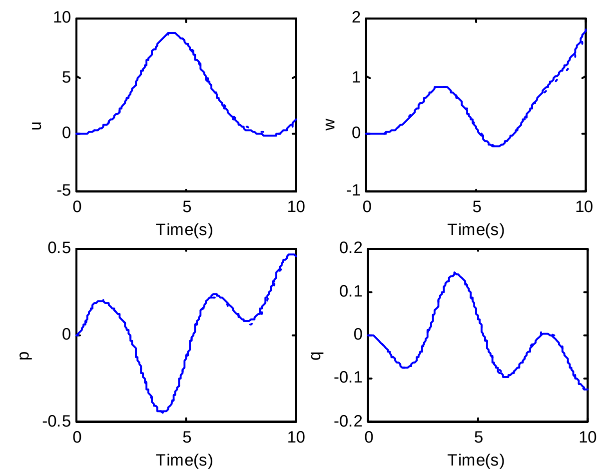

Figure 6. Case 2. Identification of Load Dynamic Model Using Rigid-Body Helicopter Model With No Parameter Errors or Measurement Noise

Note that the simulation runs are plotted for 10 seconds in the previous two cases. However, only the first 2.5 seconds of the simulation are plotted in Fig. 7 to focus on the region of most accurate identification. This figure indicates that, in general, satisfactory identification is achieved for the model with identified load dynamics included when compared to the model in which load effects are ignored. The responses for the helicopter model alone diverge from the "truth" model responses almost immediately. However, the responses of the model which includes the identified load dynamics closely matches the "truth" responses for nearly two seconds (the vertical velocity, w, response gives the poorest match to the "truth" of all nine rigid body states). From previous ID and reconfigurable control design efforts, model identification which results in accurate one to two second predictions should be adequate for control of the system.

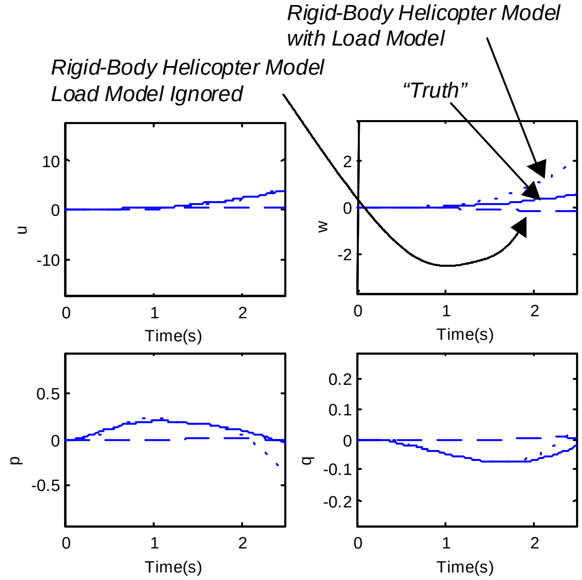

Figure 7. Case 3. Identification of Load Dynamic Model Using Rigid-Body Helicopter Model *With* Parameter Errors and Noisy Measurements

Fig. 8 presents predictions of four elements of the z-vector for Case 3. As with the helicopter state predictions shown in Fig. 7, this figure shows good prediction performance for approximately two seconds. (Although not shown, results for z_2 and z_6 are similar.) Predictions of these elements must be accurate if these states are to be included in a cost function used for control law design. Again, driving the rates of the *total* z-vector elements to zero implies that the external-load motion is stabilized. This is equivalent to regulating the small perturbations of the z-vector.

Next, the on-line identification performance is analyzed. Here, the identification algorithm is provided new measurement information and allowed to continually adapt to changes in the dynamics. Fig. 9 presents the z-states for one particular experiment. Here, the identified model is simulated forward for 0.5 seconds at each time step. Or, its prediction horizon is 0.5 seconds. At 5 seconds into the trajectory, an abrupt change in the model parameter in M_α occurs. For comparison, a model was identified off-line with the original system measurements. This model was then fixed and integrated forward for the full 10 seconds to represent a system with no on-line identification. Note that the Case 3 identified system is used here. That is, the reduced-order helicopter model was used along with parameter errors and measurement noise.

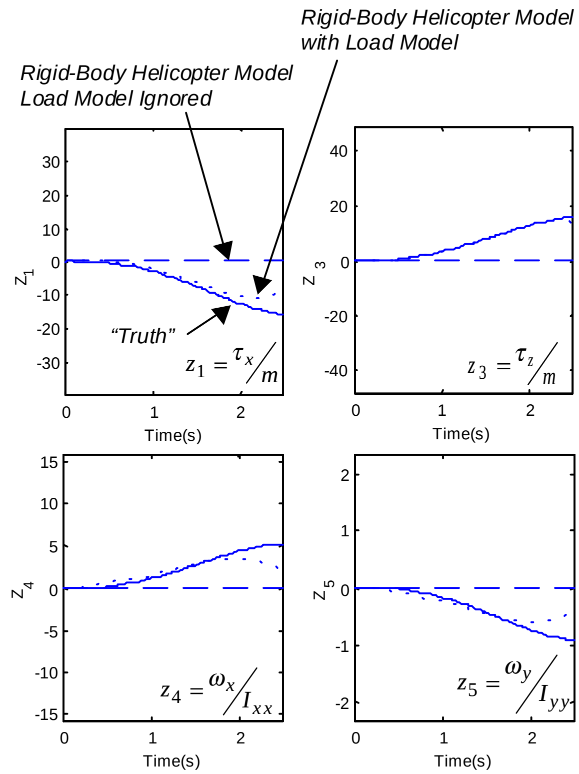

Figure 8. z-Vector Predictions For Case 3

It can be seen that the on-line identification procedure allows the model to adapt to the change in dynamics, and begins to follow the “true” system’s responses after the change in M_α. As more time elapses and with more excitation, the model identification should become more accurate. On the other hand, for the case with no on-line identification, large errors are seen almost immediately after the change in dynamics. This demonstrates the MSLS algorithm’s ability to identify changes in the dynamics and adapt the model to these changes. This aspect of the algorithm is of great importance for this application. MSLS can be used to “learn” different load dynamics as each new load is acquired. The MSLS algorithm can also be utilized if the vehicle/load system dynamics change in character as the flight condition changes (ex. as the helicopter transitions from hover to forward flight, or as the forward speed varies).

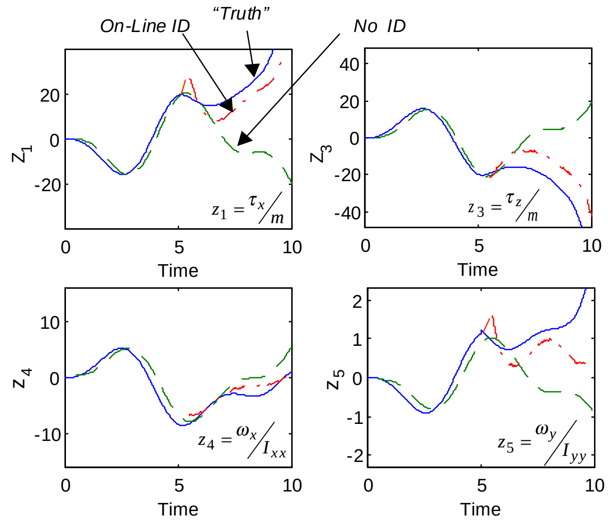

Figure 9. Case 3 On-Line Identification Results – Abrupt Model Parameter Change at 5 Seconds

Preliminary Control Results

A preliminary control study was performed using the same helicopter/external-load system studied for the identification algorithms. The approach is known as Receding Horizon Optimal (RHO) control, and results in a control law well suited for nonlinear system tracking control.[5] The two main features of this approach are:

1. a finite-time linear optimization problem is recalculated at each step, and
2. time-varying linear dynamics and short prediction horizons accurately account for system nonlinearities.

The RHO algorithm incorporate a time-varying model of the current system dynamics obtained by the MSLS algorithm. The RHO control module first *predicts* future system states, and then computes a set of effector commands based on a finite-time optimal control solution that minimizes the error between predicted plant dynamics and the desired plant responses. This minimization results in a sequence of optimal control commands, and the first command, corresponding to the current time, is applied to the system. At the next control update, rather than applying the second command in the open-loop optimal command sequence, the finite horizon optimization is completely recalculated using up-to-date estimates of the plant dynamics, desired control, and system states. In this way, the open-loop finite-horizon optimal control problem becomes closed-loop, and the optimization horizon is said to *recede* because the controller never applies the commands corresponding to the end of the horizon

For this preliminary study, the MSLS parameter identification was not integrated with the controller. It is further assumed that the controller has perfect knowledge of the coupled airframe/external-load dynamics, and that full state-feedback of helicopter rigid-body, kinematic, and rotor states, and load states was available. We recognize that these simplifying assumptions clearly improve the controller's performance, and performance degradations will most likely be seen with more realistic conditions, such as modeling errors, measurement noise and non-full-state feedback. However, the preliminary results are quite promising for this difficult control problem - in which the open-loop system is unstable in the hover flight condition. Figs. 10 and 11 present simulation results for this case study. Approximate step commands of 30 ft/sec for forward, lateral and vertical velocities of the rotorcraft were commanded in an overlapping manner. Fig. 10 shows almost perfect tracking of the commands. Fig. 11 shows the "forward" element of the relative position vector between the vehicle and the external load. (Similar results were seen for the other two elements of this relative position vector.) The elements of this vector are small perturbation quantities. Therefore, the load is at its nominal reference position when the relative position vector is zero. Hence, for stable load motion, it is desirable for this vector and its rate to be near zero. Fig. 11 indicates that the RHO control approach stabilizes the load motion and drives this state to zero.

Conclusions

Reconfigurable control is intended to provide real-time adaptation to imperfect characterizations of aircraft in new flight regimes as well as to unforeseen airframe and effector damage. The reconfigurable control and on-line identification methodology is recognized as an excellent candidate for rotorcraft transporting a variety of external-loads with unknown dynamics that become highly coupled with the rotorcraft's dynamics in flight. A method to identify the system dynamics on-line and provide the parameters in a form suitable for control is essential to operate safely and efficiently in these situations where there is incomplete knowledge of the system and no prior assumptions have been made regarding the characteristics of the load.

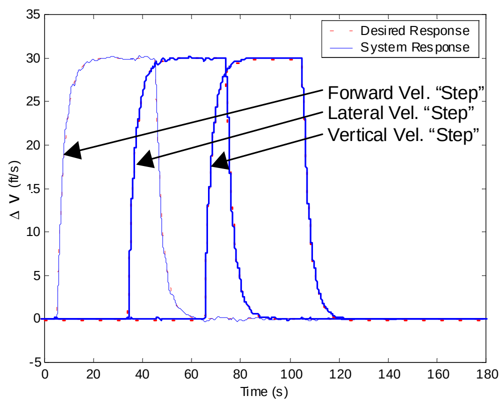

Figure 10. RHO Control Results - Commanded and Actual Velocity Responses

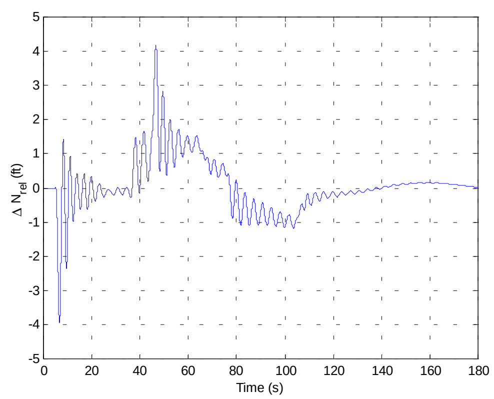

Figure 11. RHO Control Results - External Load "Forward" Relative Position Response

This paper presented a proof-of-concept study of an identification technique to model the external-load's effects on the rotorcraft. Not only are the load dynamics unknown, but the load state measurements (such as position, velocity and attitude) are unavailable. The challenge here was to represent the load's effects in a manner that is measurable. This was overcome by representing the load dynamics in terms of the forces and moments imparted to the helicopter by the tension in the cable that carries the load. The Modified Sequential Least Squares identification approach was used to estimate the load dynamics represented in this fashion. Simulation results of the identified system showed good prediction performance for one to two seconds into the trajectory. This should be an adequate prediction window for a successful feedback control design. The need for identifying load dynamics was shown to be evident. The highly interactive nature of the rotorcraft/load dynamic system requires inclusion of an identified load model for accurate predictions of the system responses.

Acknowledgements

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