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# Identification of System, Observer, and Controller from Closed-Loop Experimental Data

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**This paper considers the identification problem of a system operating in a closed loop with an existing feedback controller. The closed-loop system is excited by a known excitation signal, and the resulting time histories of the closed-loop system response and the feedback signal are measured. From the time history data, the algorithm computes the Markov parameters of a closed-loop observer, from which the Markov parameters of the individual open-loop plant, observer, and controller are recovered. A state-space model of the open-loop plant and the gain matrices for the controller and the observer are then realized. The results of the paper are demonstrated by an example using wind tunnel aircraft flutter test data.**

## Introduction

A BASIC purpose of system identification is to compute a mathematical model of a physical system based on its input-output data. The problem of minimal state-space model identification has been studied extensively in the literature in the past few decades. Current methods, such as the eigensystem realization algorithm (ERA),[1,2] have been successfully applied to identification of flexible structures. Special data are required for system identification, such as pulse response data or free decay data. If the system response to a certain rich input is available, the fast Fourier transform (FFT) technique can be used to compute the pulse response functions, which are then used to compute a state-space model of the open-loop plant. However, the process of transforming the data to the frequency domain by the FFT technique places stringent requirements on the characteristics of the data record such as the input be rich enough to ensure computational accuracy.

Recently, a method was developed to compute the Markov parameters of a linear system, which are the same as its pulse response samples.[3-6] Referred to as the observer/Kalman filter identification algorithm (OKID), the method is formulated entirely in the time domain, and is capable of handling general response data. A fundamental difference in this approach is the introduction of an observer in the identification equations. This makes identification possible not only for the open-loop plant, but also for an associated observer which can later be used in controller design. Depending on the noise characteristics, the method identifies a deadbeat observer which is the fastest possible observer in the absence of noises, or a Kalman filter which is an optimal observer in the presence of noises, or any other observer with user-specified poles. The method has been successfully applied to the identification of real systems, including a ten-bay experimental truss article at NASA Langley Research Center,[6,7] a linear model of the Space Shuttle remote manipulator based on a nonlinear simulation code,[8] and the Hubble space telescope?

An important feature of this paper is the extension of the aforementioned method to the identification of closed-loop systems. The closed-loop system includes the plant and the existing controller and/or observer. There are several instances when such a need arises. The system may be operating in a closed loop, and only closed-loop data is available for identification. An open-loop model of the plant may need to be identified from closed-loop data for the purpose of structural analysis or controller redesign. Certain plants are inherently unstable. For such plants, it may not be desirable or even possible to remove the existing feedback control system to a perform open-loop identification. Furthermore, a closed-loop identification procedure should provide not only the open-loop model, but also the existing feedback gain for controller analysis or evaluation.

This paper presents a technique that identifies a control system operating under closed-loop conditions with an existing feedback controller, which may or may not include feedback dynamics. The controller and the open-loop plant dynamics are assumed to be unknown. The closed-loop system is excited by a known excitation signal, and the closed-loop plant output responses and the feedback signal are measured. A schematic diagram of the existing or actual closed-loop system is given in Fig. 1 which shows the measured quantities, and the open-loop plant in state-space representation given by the matrices $\boldsymbol{A}$, $\boldsymbol{B}$, C, and $D$. An algorithm is developed to identify the open-loop plant, an observer gain, and the existing controller gain matrices from closed-loop test data which include the time histories of the excitation signal, the resulting closed-loop response, and the feedback control signal. The technique assumes the identified controller to be of a full-state feedback type. A schematic diagram of the identified or effective closed-loop system is shown in Fig. 2, where $\boldsymbol{A}$, $\boldsymbol{B}$, C, and $D$ again represent the identified open-loop plant, and G and $F$ represent the identified observer and controller gains, respectively. The method first identifies the Markov parameters of a closed-loop observer, which in turn produce the Markov parameters for an observer, the open-loop plant, and the controller. The approach used in this paper is similar to that for the observer/Kalman filter identification (OKID) algorithm. This paper can be considered a natural extension of the OKID for a closed-loop system. In the absence of noises, the open-loop plant and the full-state feedback gain can be identified exactly, but the observer is a deadbeat observer. In the presence of noises, the identified observer and controller are strongly influenced by the characteristics of the affecting noises. When the actual closed-loop system is not a full-state feedback type, the method will identify the effective open-loop plant and the corresponding observer/controller combination. The case where the identified closed-loop system does not assume a

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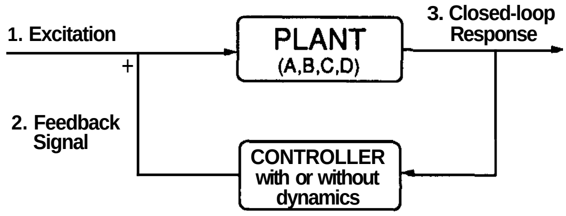


**Fig. 1 Existing (actual) control system.**

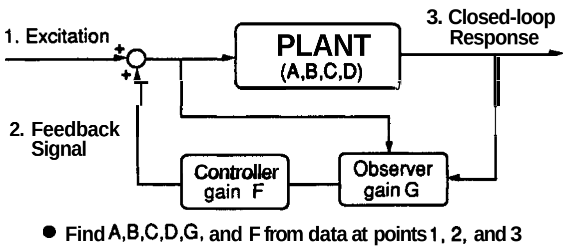


**Fig. 2 Identified (effective) control system.**

full-state feedback structure, but rather a controller with known output feedback dynamics, is treated in Ref. 10. The mathematical formulations for these two cases are different since the former case deals with known feedback control signals, whereas the latter case deals with known feedback controller dynamics.

The outline of the paper is as follows. Following this introduction, the mathematical section will describe a formulation of the closed-loop system via an observer, from which the closed-loop observer/controller Markov parameters are identified. From the observer/controller Markov parameters, the individual plant, observer, and controller gain Markov parameters are computed by a set of recovery equations to be developed in the paper. These Markov parameters are used to simultaneously realize a state-space model of the open-loop plant and its observer and controller gain matrices. The proposed method is illustrated by using a wind tunnel flutter suppression model to identify an unstable plant.

## Mathematical Formulation

### System Description

Given a linear plant which can be described by the discrete-time model

$$x(k+1)=Ax(k)+Bu(k)$$
$$y(k)=Cx(k)+Du(k) \tag{1}$$

where $x$ is an $n \times 1$ state vector, $u$ an $m \times 1$ control vector, $y$ a $q \times 1$ measurement vector, and $k$ the time index. The matrix $A$ is the state matrix, $B$ the control influence matrix, $C$ is the output influence matrix, and $D$ the direct transmission matrix. Assuming for the moment that the input $u(k)$ to the plant is simply the feedback control input $u_f(k)$ provided by an actual full-state feedback controller with a gain $F$,

$$u(k)=u_f(k)=-F\hat{x}(k) \tag{2}$$

where the state vector $x(k)$ is provided by a state estimator with a gain G,

$$\hat{x}(k+1)=A\hat{x}(k)+Bu(k)-G_e\left[y(k)-\hat{y}(k)\right]$$
$$\hat{y}(k)=C\hat{x}(k)+Du(k) \tag{3}$$

To identify this controlled plant directly from input and output data, the closed-loop system has to be excited either by an initial condition or by an excitation source. Let the closed-loop system be excited by an excitation signal $r(k)$ added to the control force $u_f(k)$. The input $u(k)$ to the plant becomes

$$u(k)=u_f(k)+r(k)=-F\hat{x}(k)+r(k) \tag{4}$$

The existing observer for the plant is still the same as before in Eq. (3), except that $u(k)$ is now given by Eq. (4) instead of Eq. (2). The system input-output relation given in terms of the observer and controller system becomes

$$\hat{x}(k+1)=(A+G_eC)\hat{x}(k)+(B+G_eD)u(k)-G_ey(k)$$
$$\hat{y}(k)=C\hat{x}(k)+Du(k) \tag{5}$$
$$u_f(k)=-F\hat{x}(k)$$

### Identification of Observer/Controller Markov Parameters

For simplicity of notations, define

$$\bar{A}_e=A+G_eC, \qquad \bar{B}_e=[B+G_eD \quad -G_e]$$
$$\bar{C}=\begin{bmatrix} C \\ -F \end{bmatrix}, \qquad \bar{D}=\begin{bmatrix} D \\ 0 \end{bmatrix} \tag{6}$$

Equation (5) becomes

$$\hat{x}(k+1)=\bar{A}_e\hat{x}(k)+\bar{B}_e\begin{bmatrix} u(k) \\ y(k) \end{bmatrix}$$
$$\begin{bmatrix} \hat{y}(k) \\ u_f(k) \end{bmatrix}=\bar{C}\hat{x}(k)+\bar{D}u(k) \tag{7}$$

where $u(k)$ is given in Eq. (4). Under the assumption that the existing observer is asymptotically stable, the relationship between $u(k)$, $y(k)$, and $\hat{y}(k)$, $u_f(k)$ can be expressed in terms of a finite number of the Markov parameters of the existing observer/controller system in Eq. (7) as

$$\begin{bmatrix} \hat{y}(k) \\ u_f(k) \end{bmatrix}=\sum_{i=1}^{\ell}\bar{Y}_e(i)v(k-i)+\bar{D}u(k) \tag{8}$$

where

$$v(k)=\begin{bmatrix} u(k) \\ y(k) \end{bmatrix}, \qquad \bar{Y}_e(0)=\bar{D}$$
$$\bar{Y}_e(k)=\bar{C}\bar{A}_e^{k-1}\bar{B}_e, \qquad k=1,2,\ldots,\ell$$

Note that for Eq. (8) to be valid, the initial condition for the observer is assumed to be zero, $\hat{x}(0)=0$, the value $\ell$ is sufficiently large such that the existing observer has converged, i.e.,

$$\bar{C}\bar{A}_e^{k}\bar{B}_e\approx 0, \qquad k\geq\ell \tag{9}$$

Suppose that a set of measurements, $u(k)$, $y(k)$, $\hat{y}(k)$, and $u_f(k)$, $k=0,1,2,\ldots,N$ is available. Equation (8) can be written in matrix form as

$$\hat{y}_e=\bar{Y}_eV \tag{10}$$

where

$$\hat{y}_e=\begin{bmatrix} \hat{y}(0) & \hat{y}(1) & \cdots & \hat{y}(\ell) & \hat{y}(\ell+1) & \cdots & \hat{y}(N) \\ u_f(0) & u_f(1) & \cdots & u_f(\ell) & u_f(\ell+1) & \cdots & u_f(N) \end{bmatrix}$$
$$\bar{Y}_e=\left[\bar{D} \quad \bar{C}\bar{B}_e \quad \cdots \quad \bar{C}\bar{A}_e^{\ell-1}\bar{B}_e\right]$$

$$V=\begin{vmatrix} u(0) & u(1) & \cdots & u(\ell) & u(\ell+1) & \cdots & u(N) \\ & v(0) & \cdots & v(\ell-1) & v(\ell) & \cdots & v(N-1) \\ & & & & & & \\ & & & v(0) & v(1) & \cdots & v(N-\ell) \end{vmatrix}$$

Provided that the available data sequences are sufficiently rich such that $Y$ is full row-rank, the Markov parameters of the existing observer/controller system can be uniquely identified from

$$\bar{Y}_e = \hat{y}_e V^T (V V^T)^{-1} \tag{11}$$

Equation (11) assumes that data from the beginning is used in the computation. In fact, one can start with data from a different time step, say $s$, by deleting the first $s$ columns in $\hat{y}_e$ and $V$ that correspond to data prior to that time step. However, this has an effect on the ability to identify the existing observer, which is discussed later.

It is important to note that information regarding the existing observer is available in $\hat{y}(k)$ starting from the beginning with $k=0$. There are certain cases in which it is not possible to recover the existing observer by Eq. (11). First, if the system starts with zero initial condition, $x(0)=0$, then it can easily be seen from Eqs. (5) and (1) that $\hat{x}(k)=x(k)$, $\hat{y}(k)=y(k)$ at all time steps. Therefore, information regarding the existing observer is not present in the data. Second, if data after the existing observer has converged is used, then the estimated output $\hat{y}(k)$ is the same as the actual output $y(k)$. Again, information regarding the existing observer is not present in the data. Third, in practice, the estimated output provided by the observer is usually not available for identification of the existing observer. The following section considers the case where only the excitation signal $r(k)$, the feedback control input $u_f(k)$, and the actual closed-loop response $y(k)$ are used in the identification problem. Consequently, the resultant solution will not yield the existing observer but rather a different observer that can be understood by the following consideration.

Consider the case where the existing observer has converged to provide the correct state of the plant. The plant and the controller can be expressed as

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ u(k) &= u_f(k) + r(k) \\ u_f(k) &= -Fx(k) \end{aligned} \tag{12}$$

Add and subtract the term $Gy(k)$ to and from the state equation in Eq. (12)

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + Gy(k) - Gy(k) \\ &= (A+GC)x(k) + (B+GD)u(k) - Gy(k) \end{aligned} \tag{13}$$

Define

$$\bar{A} = A + GC, \qquad \bar{B} = [B+GD \quad -G] \tag{14}$$

The combined system can be written as

$$\begin{aligned} x(k+1) &= \bar{A}x(k) + \bar{B}\begin{bmatrix} u(k) \\ y(k) \end{bmatrix} \\ \begin{bmatrix} y(k) \\ u_f(k) \end{bmatrix} &= \bar{C}x(k) + \bar{D}u(k) \end{aligned} \tag{15}$$

which is exactly the same as the system given in Eq. (7), except that $x(k)$, $y(k)$ now replace $\hat{x}(k)$, $\hat{y}(k)$. Note that this set of equations is only valid at time steps after the existing observer has converged, say after $s$ time steps. The corresponding version of Eq. (10) is

$$y_t = \bar{Y} V_t \tag{16}$$

where

$$y_t = \begin{bmatrix} y(s) & y(s+1) & \cdots & y(N-1) & y(N) \\ u_f(s) & u_f(s+1) & \cdots & u_f(N-1) & u_f(N) \end{bmatrix}$$

$$\bar{Y} = [\bar{D} \quad \bar{C}\bar{B} \quad \cdots \quad \bar{C}\bar{A}^{p-1}\bar{B}]$$

and for $s \le p$

$$V_t = \begin{bmatrix} u(s) & \cdots & u(p) & u(p+1) & \cdots & u(N) \\ v(s-1) & \cdots & v(p-1) & v(p) & \cdots & v(N-1) \\ \vdots & & & & & \\ v(0) & \cdots & v(p-s) & v(p-s+1) & \cdots & v(N-s) \\ & \ddots & \vdots & & & \\ & & v(0) & v(1) & \cdots & v(N-p) \end{bmatrix}$$

or for $s > p$, $V_t$ takes the form

$$\begin{bmatrix} u(s) & u(s+1) & \cdots & u(N) \\ v(s-1) & v(s) & \cdots & v(N-1) \\ & & & \\ v(s-p) & v(s-p+1) & \cdots & v(N-p) \end{bmatrix}$$

The number $p$ denotes the number of observer/controller Markov parameters $\bar{Y}(k)$ to be solved from the available data, subject to the requirement that they vanish identically after $p$ time steps, i.e.,

$$\bar{Y}(k) = \bar{C}\bar{A}^{k-1}\bar{B} \equiv 0, \qquad k > p \tag{17}$$

The least-squares solution to Eq. (16) is simply

$$\bar{Y} = y_t V_t^T (V_t V_t^T)^{-1} \tag{18}$$

Like the analysis performed in Ref. 6, the minimum value of $p$ is one such that the product $pq$ is at least equal to the order of the open-loop plant, where $q$ is the number of independent outputs. In the noise-free case if $p$ is chosen such that the product $pq$ is more than the order of the plant, then the data matrix $V_t$ is row-rank deficient. A solution can still be obtained by replacing the inverse of the quantity in the parentheses by a pseudo-inverse. In the presence of noises, however, the matrix $V_t$ tends to be full rank. The solution given by Eq. (18) is one that minimizes the Euclidean norm of the residual error

$$e = y_t - \bar{Y}V_t \tag{19}$$

To solve for $\bar{Y}$ uniquely, all the rows of $V_t$ must be linearly independent. Furthermore, to minimize any numerical error due to the computation of the pseudo-inverse, the rows of $V_t$ chosen should be as independent as possible. As a result, the maximum $p$ is the number that maximizes the number of independent rows of $V_t$.

### Computation of Plant, Observer, and Controller Gain Markov Parameters

This section describes a procedure by which the individual plant, observer, and controller gain Markov parameters arranged in the form

$$\begin{aligned} Y^{(1,1)}(0) &= D \\ Y(k) &= \begin{bmatrix} C \\ F \end{bmatrix} A^{k-1}[B \quad G] = \begin{bmatrix} CA^{k-1}B & CA^{k-1}G \\ FA^{k-1}B & FA^{k-1}G \end{bmatrix} \\ &\equiv \begin{bmatrix} Y^{(1,1)}(k) & Y^{(1,2)}(k) \\ Y^{(2,1)}(k) & Y^{(2,2)}(k) \end{bmatrix}, \qquad k = 1, 2, \ldots \end{aligned} \tag{20}$$

are computed from the following identified observer/controller Markov parameters

$$\bar{Y}(0) = \begin{bmatrix} D \\ 0 \end{bmatrix} \equiv \begin{bmatrix} \bar{Y}^{(1,1)}(0) \\ \bar{Y}^{(2,1)}(0) \end{bmatrix}$$

$$\bar{Y}(k) = \begin{bmatrix} C \\ -F \end{bmatrix} (A + GC)^{k-1}[B + GD \quad -G]$$

$$\equiv \begin{bmatrix} \bar{Y}^{(1,1)}(k) & -\bar{Y}^{(1,2)}(k) \\ -\bar{Y}^{(2,1)}(k) & \bar{Y}^{(2,2)}(k) \end{bmatrix}, \quad k = 1, 2, \dots \tag{21}$$

Note that due to the minus sign in $F$ and $G$, a minus sign is added to the off-diagonal submatrices $\bar{Y}^{(1,2)}(k)$ and $\bar{Y}^{(2,1)}(k)$ for consistency and convenience. The direct transmission term $D$ is simply the first partition of $\bar{D}$,

$$Y^{(1,1)}(0) = \bar{Y}^{(1,1)}(0) = D \tag{22}$$

It can easily be shown by the same procedure as in Ref. 6, that the plant Markov parameters $Y^{(1,1)}(k) = CA^{k-1}B$, and the observer gain Markov parameters $Y^{(1,2)}(k) = CA^{k-1}G$ can be computed from $\bar{Y}^{(1,1)}(k) = C(A + GC)^{k-1}(B + GD)$ and $\bar{Y}^{(1,2)}(k) = C(A + GC)^{k-1}G$ as

$$Y^{(1,1)}(k) = CA^{k-1}B$$

$$= \bar{Y}^{(1,1)}(k) - \sum_{i=1}^{k} \bar{Y}^{(1,2)}(i) Y^{(1,1)}(k-i) \tag{23}$$

$$Y^{(1,2)}(k) = CA^{k-1}G$$

$$= \bar{Y}^{(1,2)}(k) - \sum_{i=1}^{k-1} \bar{Y}^{(1,2)}(i) Y^{(1,2)}(k-i) \tag{24}$$

where $\bar{Y}^{(1,1)}(k) = \bar{Y}^{(1,2)}(k) \equiv 0$ for $k > p$.

To derive the recovery equations for $Y^{(2,1)}(k) = FA^{k-1}B$, and $Y^{(2,2)}(k) = FA^{k-1}G$, one proceeds analogously. For example, consider the expression for $\bar{Y}^{(2,1)}(k)$, say for $k = 3$,

$$\bar{Y}^{(2,1)}(3) = F(A + GC)^2(B + GD)$$

$$= F(A + GC)^2 B + F(A + GC)^2 GD$$

$$= FA^2B + FGCAB + F(A + GC)GCB$$

$$+ F(A + GC)^2 GD$$

$$= Y^{(2,1)}(3) + \bar{Y}^{(2,2)}(1) Y^{(1,1)}(2) + \bar{Y}^{(2,2)}(2) Y^{(1,1)}(1)$$

$$+ \bar{Y}^{(2,2)}(3) Y^{(1,1)}(0)$$

Solving for $Y^{(2,1)}(3) = FA^2B$ yields

$$Y^{(2,1)}(3) = \bar{Y}^{(2,1)}(3) - \bar{Y}^{(2,2)}(1) Y^{1,1)}(2) - \bar{Y}^{(2,2)}(2) Y^{(1,1)}(1)$$

$$- \bar{Y}^{(2,2)}(3) Y^{(1,1)}(0)$$

In general, it can be shown that the recovery equations for the controller gain Markov parameters $Y^{(2,1)}(k) = FA^{k-1}B$, and observer/controller gain Markov parameters $Y^{(2,2)}(k) = FA^{k-1}G$ are

$$Y^{(2,1)}(k) = FA^{k-1}B$$

$$= \bar{Y}^{(2,1)}(k) - \sum_{i=1}^{k} \bar{Y}^{(2,2)}(i) Y^{(1,1)}(k-i) \tag{25}$$

$$Y^{(2,2)}(k) = FA^{k-1}G$$

$$= \bar{Y}^{(2,2)}(k) - \sum_{i=1}^{k-1} \bar{Y}^{(2,2)}(i) Y^{(1,2)}(k-i) \tag{26}$$

where $\bar{Y}^{(2,1)}(k) = \bar{Y}^{(2,2)}(k) \equiv 0$ for $k > p$. Equations (23-26) constitute a set of recovery equations to compute the individual plant, observer, and controller gain Markov parameters from an identified set of observer/controller Markov parameters. These parameters are then used to realize a state-space model of the open-loop plant, and the observer/controller gain matrices.

### Realization of Open-Loop Plant, Observer, and Controller Gains

In mathematical terms, realization can be thought of as a factorization of a parameter sequence of the form $CA^{k-1}B$, to obtain a set of $(C, A, B)$ that preserves the prescribed relationship between the parameters in the sequence. Therefore, the theory is applicable to factorization of all such sequences whose parameters obey the same prescribed relationship. The eigensystem realization algorithm (ERA)[1,2] can be applied to the combined Markov parameter sequence $Y(k)$ given in Eq. (20) to compute a realization of the open-loop plant matrices, an observer, and controller gain. This can be done by first forming the Hankel matrix of $Y(k)$ as

$$H_c(k-1) = \begin{bmatrix} Y(k) & Y(k+1) & \cdots & Y(k+s) \\ Y(k+1) & Y(k+2) & \cdots & Y(k+s+1) \\ \vdots & \vdots & \ddots & \vdots \\ Y(k+r) & Y(k+r+1) & \cdots & Y(k+r+s) \end{bmatrix} \tag{27}$$

The following realization will simultaneously identify the system matrices $A$, $B$, $C$, the observer gain $G$, and controller gain $F$,

$$A = D_r^{-1/2} P_r^T H_c(1) Q_r D_r^{-1/2}$$

$$[B \quad G] = D_r^{1/2} Q_r^T E_{(m+q)} \tag{28}$$

$$\begin{bmatrix} C \\ F \end{bmatrix} = E_{m+q}^T P_r D_r^{1/2}$$

where the order of the realization is determined from the singular value decomposition of the Hankel matrix $H_c(0)$,

$$H_c(0) = PDQ^T = P_r D_r Q_r^T \tag{29}$$

The subscript $r$ refers to the matrices formed by retained columns in $P$, $Q$, and the retained singular values in $D$, respectively. The matrix $E$, is made up of zero and identity matrices defined as

$$E_\alpha^T = [I_\alpha \quad O_\alpha \quad \cdots \quad O_\alpha], \qquad \alpha = m + q \tag{30}$$

## Experimental Results

The method developed in this paper is illustrated by an example using wind tunnel aircraft flutter test data.[11] Experimental data were obtained from wind tunnel tests of an aeroelastic model with active flutter control operating. The model, known as the active flexible wing (AFW), has a digital controller which suppresses flutter by properly phased commands to actuators of eight control surfaces on the wing's leading- and trailing-edge surfaces. During flutter suppression control law testing, acceleration signals from sensors distributed on the model were first filtered for antialiasing and then quantized at a 200-Hz sample rate. The quantized signals obtained from both sides of the model were then symmetrized in pairs. These symmetrized signals became the inputs to the symmetric and antisymmetric flutter suppression control laws and also the source of the closed-loop response time histories to be used for the identification process. Output signals of the feedback control laws and independent input excitation to the wing provided the remaining time histories necessary for identification of the closed-loop control system. During tests, each of the actuator inputs was excited individually by adding the excitation signal to the feedback control output signal. This procedure allowed the generation of all of the responses neces-

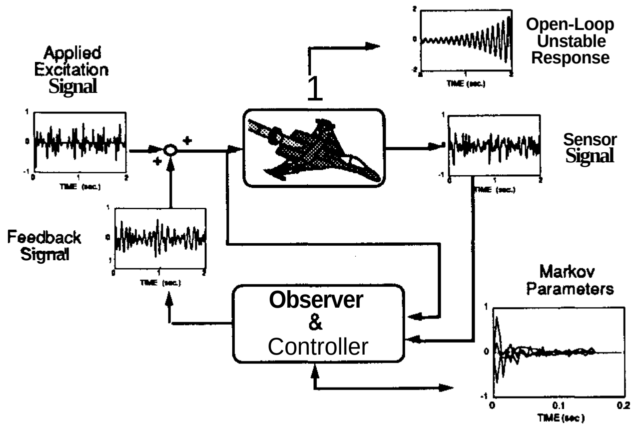


**Fig. 3 Identified (effective) control system from experimental data.**

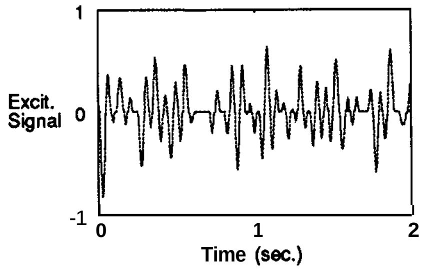


**Fig. 4 Excitation time history.**

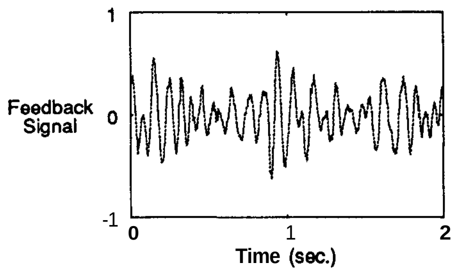


**Fig. 5 Feedback control time history.**

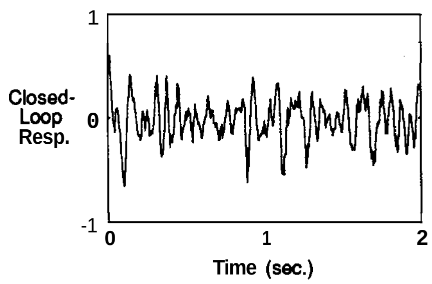


**Fig. 6 Resulting closed-loop response.**

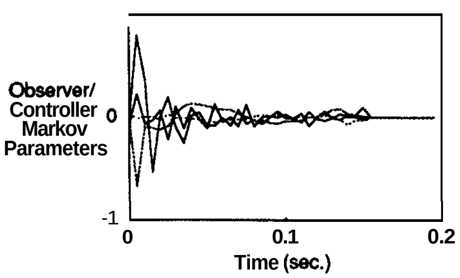


**Fig. 7 Identified observer/controlled Markov parameters.**

sary to identify the multiple-input/multiple-output control system. The excitation signals themselves were either logarithmic sine sweeps or so-called pseudorandom noise. The excitation signal, the resulting closed-loop response time histories, and the feedback control signal were used in the closed-loop technique developed in this paper to identify the AFW model including the open-loop system matrices, an observer gain, and the existing controller gain.

### Aircraft Flutter Identification

Three sets of experimental data were used corresponding to different dynamic pressure conditions: 250 psf, 260 psf, and 280 psf, respectively. Results shown in the following paragraph are for the 260-psf condition unless otherwise specified. The number of data points used in this case is 600, with a sampling interval of 0.005 s apart (200-Hz sampling rate). The AFW with a single input and single output pair is shown in Fig. 3 along with actual time histories used in the identification and the identification results, which are discussed in more detail later.

From the data histories shown in Figs. 4–6 for the first–2 s, 30 observer/controller Markov parameters arranged in $\boldsymbol{Y}$ as defined in Eq. (16) are computed using Eq. (18), assuming that the existing observer has converged after 300 time steps, i.e., $p = 30$, $s = 300$. The identified observer/controller Markov parameters are shown in Fig. 7. There are four curves in this plot, each corresponding to each elements of $Y(k)$, respectively. By letting $p = 30$, the deadbeat condition $\bar{Y}(k) = 0$ is imposed for $k > p$. The time histories of $\bar{Y}(k)$, therefore, are set to be zero after 30 time steps or $30 \times 0.005 = 0.15$ s (see Fig. 7). Using the identified observer/controller Markov parameters, the individual plant, observer gain, controller gain, and observer/controller gain Markov parameters are computed using Eqs. (23–26), which are shown in Figs. 8–11, respectively. Note that these time histories are not limited to the 0.15 s duration. In fact, by invoking the imposed deadbeat condition for the observer/controller Markov parameters, as many of these individual plant, observer gain, controller gain, and observer/controller gain Markov parameters can be recovered as desired. The pulse responses increase in amplitude with time, revealing open-loop instability.

Using the computed Markov parameters, a state-space model of the open-loop plant and the controller and observer gains are then computed. The plant Markov parameters are simply its pulse response samples. The flutter mode is then identified by solving the eigenvalues of the open-loop state matrix. The identified flutter mode for the 260 psf condition shows an open-loop frequency of 8.78 Hz and 3.34% negative damping, implying open-loop instability. This example illustrates the case where open-loop identification may not be possible or practical for such a plant. Similar analysis performed on the two remaining sets of data revealed that the identified flutter mode for the 250 psf condition has an open-loop frequency of 9.06 Hz and 0.26% negative damping, indicating marginal open-loop instability. The final condition, 280 psf, was shown to have an open-loop frequency of 8.76 Hz and 5.73% negative damping, indicating even greater open-loop instability. Comparison of the identified results with the analytical results showed excellent agreement in frequencies and damping, indicating a coalescing mode switch in frequency.

### Discussion

In general, a specific (or existing) observer is not identifiable because the observer becomes ineffective when the transient responses decay out and the errors between the true states and the estimated states become dominated by the plant uncertainties and measurement noises. Therefore, from given excitation signals, feedback signals, and measurement data, one identifies an effective observer as determined by the plant uncertainties and measurement noises instead of the specific observer. However, this does not influence the identification of the open-loop plant and the feedback controller gain. When the

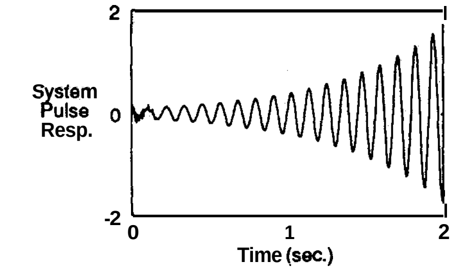


**Fig. 8 Recovered plant Markov parameters (plant pulse response samples).**

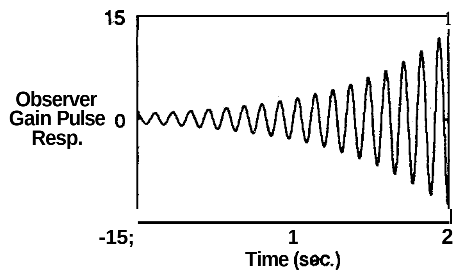


**Fig. 9 Recovered observer gain Markov parameters.**

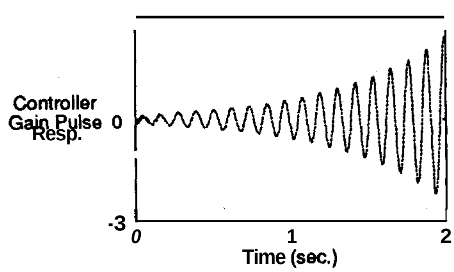


**Fig. 10 Recovered controller gain Markov parameters.**

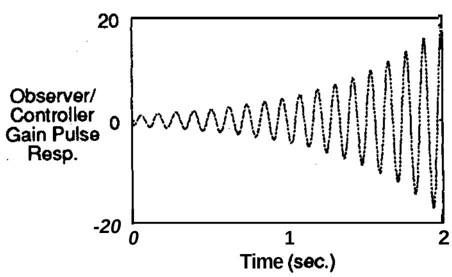


**Fig. 11 Recovered observer/controller gain Markov parameters.**

data length is sufficiently long, and the number $p$ is chosen to be sufficiently large, then the identified observer tends to a Kalman filter which may not be the observer given by the controller designer. Also, numerical studies indicate that this technique works particularly well for unstable plants because the signal-to-noise ratio for an unstable mode is generally higher than that for a stable mode.

## Concluding Remarks

A technique is developed for the identification of a closed-loop system from experimental data. This technique works for stable and unstable plants such as the case in the aircraft flutter tests where the open-loop plant is unstable but the closed-loop system with a feedback controller is stable. As long as the excitation signals such as a random signal or a sine-sweep signal are sufficiently rich, the identified results are unbiased and very accurate if the plant uncertainties and measurement noises are white, zero-mean, and Gaussian. Studies from a few sets of wind tunnel aircraft flutter test data suggest that this technique should be very useful in aircraft system identification.

## Acknowledgment

This method was originally motivated and developed for the identification of a closed-loop system for control of large space structures. Anthony S. Pototzky of Lockheed Engineering and Sciences Company has provided the flutter test data for a possible application in the aircraft flutter identification. Pototzky is currently working on the comparison of this method with other existing methods.

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