Flexible Spacestructure Control
Via Moving-Bank Multiple Model Algorithms

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I. INTRODUCTION

Presented here is the design of a moving-bank multiple model adaptive controller (MMAC) implementing a parallel bank of Kalman filters and LQG (linear system model, quadratic cost, and Gaussian noise models) controllers that quells oscillations introduced in a large flexible space structure. During the presentation the space structure and the corresponding system models are discussed, along with why adaptive algorithms are implemented. A foundation of what a MMAC is, is also presented. This latter discussion then leads to the presentation of the moving-bank MMAC.

II. STRUCTURE

The structure under examination is model two of the Space Integrated Control Experiment (SPICE) structure [5]. The model was received from Phillips Laboratory, Kirtland Air Force Base, New Mexico. The SPICE structure model consists of 486 elements connected at 371 nodes and can be divided into three major structural sections. The hexagonal base of the structure, also called the bulkhead, is 6.19 m in diameter and has a deformable mirror mounted upon it. Three legs (tripod) connect the bulkhead to the smaller secondary mirror assembly (SMA) which is 1.32 m in diameter and whereupon a smaller mirror is mounted. The overall height of the structure is 8.14 m.

Ensuring the SMA and the bulkhead are aligned is of vital importance; thus, measuring and reducing linear and angular displacement is the purpose of the sensors and actuators. An exaggerated example of the bulkhead and SMA not being aligned is shown in Fig. 1. Note that the alignment is not altered by a pure torsional force about the line of sight (LOS) axis.

The actuators employed are called proof mass actuators (PMAs). A PMA has a mass that is moved by an electromagnetic force. This mass is moved to inhibit the bending of the structure at the location of the PMA. There are 18 PMAs located on the structure. Six are mounted in a vertical position at each of the “hexagonal points” on the bulkhead. The remaining 12 PMAs are located on the tripod. Each leg of the tripod has an x-axis and y-axis PMA located at one-third and two-thirds the length of the leg. Accelerometers are used to measure the bending of the structure induced by disturbances entering the structure. There are 18 accelerometers, one collocated with each PMA. There are also assumed to be six disturbances, one entering at each of the six ends of the tripod.

III. MODEL

This section describes the individual components of the system and the contribution each has on the
Fig. 1. Bending structure example [5].

Fig. 2. SPICE system block diagram.

complete system. A block diagram of the complete system is displayed in Fig. 2. From the figure, the only block with a measurement output vector is the accelerometers, but two filter measurement matrices are implemented in the MMAC design for comparison. The first is the measurement matrix as stated previously, a measurement matrix representing only accelerometer measurements (referred to as the original $H$ matrix). The second measurement matrix (expanded measurement matrix) includes the relative velocities and positions of the PMAs as well as the acceleration measurements. The LOS block determines the alignment error in the “$x$” and “$y$” coordinates which are used for error analysis. The LOS information is not used as measured quantities for feedback in the controller, but the LOS variables are explicitly weighted in the formulation of the cost for the LQG controller synthesis.

The size of the overall system model in modal coordinates obtained from Phillips Laboratory is 352 states for a structure model that represents the first 56 bending modes. The size of this model would be computationally burdensome, so reducing the size of the model is necessary. During the descriptions of the system components, the model reduction is described.

Disturbances: The shaping filter that forms the $n$ disturbance inputs of Fig. 2 passes white noise over the 31.416 to 62.832 rad/s frequency band. Since this notch filter is a fourth-order model that shapes six white noise inputs of equivalent strength, this filter contributes 24 states to the overall system model. The disturbances for the SMA represent the motion of cooling fluid in the structure [1]. The disturbance due to the motion of the fluid could have been modeled many different ways. This model, with each axis disturbance entering a separate tripod leg, is the particular model chosen by Phillips Laboratory.

Proof Mass Actuators: The 18 PMAs were initially modeled with 144 states, requiring four states for each errorless PMA model and four states to model the error for each PMA. The high number of states for the overall PMA initial design was too large for effective computer simulation. Thus, the initial design was altered to reduce the number of states required to describe the PMAs. Examination of the low-pass filters indicated that the PMA was passing frequencies below 6284.9 rad/s and the noise was being shaped at frequencies below 3141.66 rad/s; these low-pass frequencies are much larger than 628.32 rad/s, or 100 Hz, which is the maximum frequency of interest for this study. Oscillations with frequencies greater than 628.32 rad/s are assumed to be “instantaneously” quelled by passive damping designed into the structure. Therefore, the two low-pass filters were eliminated from the design. Bode plots were then constructed for the remaining high-pass filters to see if a further consolidation could be accomplished. These plots indicated that the noise and command plots are of identical shape and only vary by a constant. Therefore, a gain-corrected white noise summed with the command prior to entering the filter was chosen as the new PMA design. Thus, the overall state contribution becomes 36 states: 18 PMAs each requiring a two-state high-pass filter model.

Accelerometers: The original model of the accelerometers consisted of 72 states. Again, as in the PMA model, the noise model includes a low-pass filter that becomes effective outside the high-frequency point of interest. Therefore, the low-pass filter was extracted, resulting in a three-state accelerometer model for each of the 18 inputs, or a total of 54 states. The retained high-pass filter removes low frequencies attributed to rigid body motion.

Overall Model: Thus, the overall state vector dimension of the system truth model is 114 + 2$n$, where $n$ is the number of structural modes being modeled (a position and velocity state are included for each node). For the reduced-order models, the
disturbances are replaced with white noise and the accelerometer low-frequency rolloffs were ignored, resulting in state contributions from these subsystems of zero states for the disturbances model and 18 states for the accelerometers' first-order lag response model. Thus, the overall system dimension of the reduced-order filter model is \(54 + 2n\).

**Line of Sight:** The LOS outputs are obtained from an optical scoring system. This system uses 39 precisely placed laser and sensor pairs to determine a change in position of a laser with respect to the corresponding sensor. Each LOS optical element output reflects alignment change of a particular laser/sensor pair. These outputs are then transformed by a transformation matrix to "X" and "Y" LOS errors, as depicted in Fig. 2.

**Structure:** The structural truth model was attained from the mathematical representation of the SPICE structure received from the Phillips Laboratory, delivered in the modal coordinate system [5]. This is a very desirable form because it allows direct access for modeling to parameters that may vary, in particular the undamped natural frequency and the damping ratio. Also the modal coordinate form is convenient for developing reduced-order models of the structure. A description of the transformation process from physical coordinates to modal coordinates, along with the relationship of the mass and stiffness parameters of the physical form to the undamped natural frequency and damping ratio parameters of the modal form, are discussed in [2].

Three different mathematical models were delivered by the Phillips Laboratory. Examination of them indicated that the two smaller models were constructed by implementing modal reduction on the 93-mode model. The decision was made to declare one of the three models received as the structural "truth model" for this study. Recalling that the frequency range of significance for this structure is approximately 0 to 100 Hz, and that the overall system model dimension is \(114 + 2n\), the 40-mode model was selected. This reduces the number of structure truth model states by 106 and therefore the overall system states to 194, while retaining the dominant frequencies. The corresponding filter/controller design model then has 134 states.

**IV. WHY ADAPTIVE ALGORITHMS?**

In the design process of the space structure, the exact mass and stiffness of the final product are not known precisely. Also once the structure is in orbit the mass and stiffness parameters may vary due to fluid flow, fuel depletion, physical failures, continual bending, and age. Thus the corresponding undamped natural frequency \(\omega\) and damping ratio \(\zeta\) parameters of the modal structure model may take on a range of values.

A Kalman filter and LQG controller were developed for the nominal \(\zeta\) and \(\omega\) parameters. A robustness test was then initiated by varying the \(\omega\) parameters in the "truth model" without altering the filter/controller. The results of this test indicated that the natural frequency parameters could be increased only by two percent before the system became unstable [2]. The lack of robustness and the possibility of a wide range of parameter values indicate a strong need for an adaptive system.

**V. MULTIPLE MODEL ADAPTIVE CONTROL**

**Overview:** MMAC is a technique that adapts to the effects of the uncertain parameters [6]. The basic principle is to generate an LQG controller for each discrete (or discretized) value of the vector of uncertain parameters. These elemental controllers are then set up in a parallel configuration (called a bank), as illustrated in Fig. 3. Note that two outputs are taken from each Kalman filter in the bank. The first is the state estimate based upon the parameter value assumed by the filter and the second output is the residual. The residual is used to determine which of the filter models is most "correct." The filter model that best estimates the true state value of the system has a small residual magnitude (relative to the filter-computed residual covariance), while a filter model based upon an incorrectly assumed parameter value has a larger residual magnitude [6]. The residual value of each filter is utilized to determine a weighting factor for the corresponding state estimate, namely, the hypothesis conditional probability that the real parameter assumes the particular discrete value used as a basis for that filter design. The conditional probability that is associated with a good filter model (small residual) will be greater than the probability for a poor filter model (large residual) [6].

The conditional probabilities \(p_k(t_i)\) for \(k = 1, 2, \ldots, K\) are determined by the recursion:

\[
p_k(t_i) = \frac{f(a_k)z(t_i-1) | a_k, z(t_i-1)p_k(t_i-1)}{\sum_{j=1}^{K} f(a_j)z(t_i-1) | a_j, z(t_i-1)p_j(t_i-1)}
\]

where \(a_k\) is each parameter value for \(k = 1, 2, \ldots, K\), and \(K\) is the number of Kalman filters; \(z(t_i)\) is the measurement at time \(t_i\), whereas \(z(t_i-1)\) is the previous measurement history composed of \(z(t_i)\) through \(z(t_{i-1})\). The first numerator term in (1) is the probability density of the current measurement based on the assumed parameter value and the observed past measurement history. This probability density function is computed by

\[
f(a_k)z(t_i-1) | a_k, z(t_i-1) = \frac{1}{(2\pi)^{m/2} | A_k(t_i) |^{1/2}} \exp\left\{-\frac{1}{2} x_k^T(t_i)A_k^{-1}(t_i)x_k(t_i)\right\}
\]

(2)
where $r_k(t)$ is the residual $[z(t) - H_k(t)\hat{x}_k(t^-)]$ in the $k$th filter, and $A_k(t) = [H_k(t)P_k(t^-)H_k^T(t) + R_k(t)]$. The $k$th filter residual $r_k(t)$ is dependent upon the current measurement $z(t)$, the measurement matrix $H_k(t)$, and the state estimate $\hat{x}_k(t^-)$, before the $i$th measurement. The state estimation error covariance matrix before the $i$th measurement $P_k(t^-)$, the measurement matrix and the measurement noise covariance matrix $R_k(t)$, are used to construct $A_k(t)$, the filter-computed residual covariance.

The denominator of (1) represents the sum of the numerator terms computed at time $t_i$. This ensures that the sum of the conditional probability (weighting factor) $p_k$ values is always one. However, a concern exists with the weighting factor equation. If for any reason the conditional probability $p_k$ for a particular filter should become zero, then $p_k$ becomes "locked" at a zero value for all time thereafter. Changing the real world conditions will not unlock the weighting factor of zero, even if the filter is estimating a good state value. The cause of this effect is that (1) multiplies the previous value of $p_k$ by the first term in the numerator. A lower limit (threshold) on computed $p_k$ is set to avoid the zero lock-in condition from occurring.

Bayesian Estimation: An uncertain parameter $a$ can affect the estimation of a state by making it difficult to determine the matrices which describe the system, since deterministic knowledge of the parameter values is necessary to obtain highest precision for the state estimation. The purpose of a Bayesian estimator is to compute the conditional density of $x(t)$ and $a$ given the measurement history:

$$f_a[x(t_i)|Z(t_i), a] = f_a[x(t_i)|Z(t_i), a]f_a[Z(t_i)|a]$$

(3)

If $a$ can assume any value over a continuous range, $A \subset \mathbb{R}^p$, an infinite number of Kalman filters would be required to represent every possible point value in $A$. Since an infinite number of filters is not feasible, the parameter space is discretized. The result is that the parameter value $a$ takes on a finite set of values $\{a_1, a_2, \ldots, a_K\}$, which are located throughout a space of reasonable parameter values, and an LQG controller algorithm is generated for each discrete parameter value, $a_k$.

Examining (3), the first term on the right is the Gaussian density function that is totally definable in terms of the estimate $\hat{x}_k(t_i^-)$ and the error covariance $P_k(t_i^-)$ produced just after the $i$th measurement by each Kalman filter generated assuming that $a = a_k$.

The second term is given as

$$f_a[Z(t_i)|a] = \sum_{k=1}^{K} p_k(t_i)\delta(a - a_k)$$

(4)

and $p_k(t_i)$ is the hypothesis conditional probability that $a = a_k$, conditioned on the observed measurements to time $t_i$. The adaptive filter produces a conditioned mean state estimate defined as [6]

$$\hat{x}(t_i) = \mathbb{E}\{x(t_i) | Z(t_i) = Z_i\}$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_a[x(t_i)|Z(t_i), a] \xi d\xi d\alpha$$

$$= \sum_{k=1}^{K} \hat{x}_k(t_i^-) \cdot p_k(t_i)$$

(5)

using (3) and (4). Here $\hat{x}_k(t_i^-)$ is the state estimate produced by the Kalman filter generated for the parameter $a_k$, and $p_k(t_i)$ is the associated probabilistic weighting factor. Analogously, the MMAC control is generated as the probability-weighted average seen in Fig. 3.

The parameter value $a$ at a given time $t_i$ can be estimated by the following conditional mean value [6]:

$$\hat{a}(t_i) = \mathbb{E}\{a(t_i) | Z(t_i) = Z_i\}$$

$$= \int_{-\infty}^{\infty} \alpha f_a[Z(t_i)|a] d\alpha$$

$$= \sum_{k=1}^{K} a_k \cdot p_k(t_i).$$

(6)

The covariances of the estimated state and parameter vectors can also be generated analytically [6], but they are not required for the online MMAC algorithm.

The replacement of the $A_k(t)$ term throughout (2) with the identity matrix yields another form of computing the conditional density function.
Conceptually, it is assumed that the residuals follow a “maximally noncommitted residual distribution” [9, 10]. This density function is called the maximum entropy with identity covariance (ME/I) density computation and is given by [9]

\[ f_d(t_i | a_k, Z_{i-1}) = \frac{1}{(2\pi)^{m/2}} \exp\left(-\frac{1}{2} r_x^T (t_i) r_x(t_i)\right). \]

(7)

The ME/I density computation ensures that the residual with lowest (absolute versus relative) magnitude is given the highest probability \( p_d(t_i) \) value. The ME/I density computation is the technique implemented in this research.

**Moving-Bank MMAC Development:** The moving-bank MMAC implements a subset of the elemental filter/controllers of the full-bank MMAC and allows dynamic redeclaration of which subset is to be maintained at the current time. The concept is to keep the moving bank centered around the best estimate of the parameter in parameter space: the parameter value may not be known a priori and it may vary over time. The parameter estimate is determined to be outside the bounds of the parameter space, the bank needs to encompass the parameter estimate by either moving the bank in a finely discretized configuration to the parameter estimate or by expanding the bank in a coarsely discretized configuration to surround it. There are four decision logics that could be used to keep the moving bank centered about the estimated parameter value: 1) residual monitoring, 2) parameter position monitoring, 3) parameter position and “velocity” monitoring, and 4) probability monitoring. The threshold values referenced in this discussion are determined through empirical parameter evaluation, or “tuning.” The only decision logic discussed in this work is parameter position monitoring. The remaining decision logics are discussed in several references, notably [2, 8].

Parameter position monitoring is a technique that attempts to maintain the center of the bank in parameter space over the estimated parameter value obtained from (6). When the estimated parameter position varies from its current location, the bank moves to maintain the center of the bank as close to the estimated value as possible. If the distance from the center of the bank to \( \hat{a}(t_i) \) becomes larger than some chosen threshold, a move of the bank in that direction is applied. Fig. 4 illustrates a bank of filters initially centered in a three-by-seven parameter space (damping ratio \( \zeta \) discretized to three point values, and undamped natural frequency \( \omega \) to seven values, for the bending modes of this research). The true parameter (notated by the cross) is not at the center of the space, and the bank “moves” to the left of its original position to remain centered about the true parameter.

**LQG Controller:** MMAC design inherently involves “assumed certainty equivalence” concepts [7]: each controller gain block in Fig. 3 is designed as an LQ full-state feedback controller based on the parameter value \( a_k \), and it is then cascaded with the corresponding Kalman filter based on the same assumed \( a_k \), to form the LQG controller based on \( a_k \). For each LQG controller synthesis, the quadratic cost,

\[ J = E \left\{ \sum_{i=0}^{\infty} \frac{1}{2} [x(t_i)^T X x(t_i) + u^T(t_i) U u(t_i) + 2x^T(t_i) S u(t_i)] \right\} \]

(8)

is chosen so as to yield quick quelling of any bending vibrations while not saturating the actuators (large \( X \) and small \( U \)). Previous research results [3, 4] indicated that the cross weighting matrix \( S \) had a small magnitude value, therefore \( S \) was set to zero with no appreciable performance impact.

**Discretized Space:** When parameters do not naturally take on discrete values but a continuous range of real values, the method in which the space is discretized is important. The number of points in the parameter space equate to the number of Kalman filters and LQ controller gains required in the MMAC.

Discretization of a continuous parameter space also indicates the robustness of a single filter/controller. The parameter space discretization is accomplished by varying one parameter of the truth model at a time (e.g., the scalar multiplier of undamped natural frequencies \( \omega \) of bending modes) in one direction until the controlled system, based on the nominal parameter point, becomes unstable. This parameter variation, denoted \( \Delta \omega_1 \), is then used to generate the first new discrete value in a three-by-seven parameter space (in this study; see Fig. 4) for the MMAC. To determine the remaining parameter points in the space, the filter and truth models are modified to represent the new \( \omega \) found in the first sensitivity analysis. A sensitivity analysis is then accomplished about this new nominal parameter point by continuing the parameter variation of the truth model and determining a new \( \Delta \omega_2 \). This procedure is repeated until the parameter discretization is completed in both directions of varying the parameter from the nominal point. The same procedure is executed to determine the \( \zeta \) direction parameter points. After completing the space
discretization, the structure plant models for each point in the space can be created.

VI. RESULTS

Tuning: Tuning of the filters was accomplished visually by examining the plots of the true error mean ± one standard deviation (sigma) with the filter-computed error mean ± sigma plotted on the same plot. The filter error sigma bounds may be moved by adjusting (tuning) the dynamics noise strength $Q_f$ of the filter. The $Q_f$ values that are adjusted enter the structure at the disturbance inputs and the PMAs. In this study, the primary method of tuning $Q_f$ was accomplished by adjusting all the driving noise values by a scalar multiplier. Adjusting $Q_f$ for each noise input can be done, but by tuning all $Q_f$ together conserves the time required for tuning. This works well as long as the filter model displays very weak or no coupling in the three coordinate axes and as long as the desired one-sigma filter-computed values of the $X$- and $Y$-axis error statistics are about the same.

Tuning of the controller was accomplished by adjusting the scalar multiplier affecting the state weighting matrix, once the weighting matrix was defined so as to place quadratic penalty on the two LOS deviations seen in Fig. 2. The scalar multiplier given by [5] for the controller weighting matrix was determined to be a maximum value. The state scalar weight was adjusted until the instability point of the closed-loop system was discovered (recall that a reduced-order design model is used). Using the multiplier for the state weighting matrix to determine the instability point ensured that the "tightest" state control will be obtained for this application. Once the instability point was found, the multiplier was tuned back by 10 percent. Weighting values closer than 10 percent presented equivalent or degraded regulation of the $X$- and $Y$-axis deviations, thus a 10 percent rollback was chosen. This method of tuning provided effective control and diminished sensitivity to tuning variations.

Full-Order Structure Model: This portion of the study examined the performance of the 134-state filter model against the 194-state truth model, which were developed in Section III. The results of an open-loop simulation (no control applied) are shown in Fig. 5. The predicted deviations of the actual $X$ and $Y$ LOS variables illustrate the need for a controller (in this case an LQG controller) to quell the oscillations in the structure. The temporally averaged standard deviation values in the $X$ and $Y$ axes are greater than 20 $\mu$rad.

The simulation results for the closed-loop case using the original $H$ matrix (accelerometer measurements only) yield temporal average values of 4.38 $\mu$rad standard deviation in the $X$-axis and 4.87 $\mu$rad in the $Y$-axis. These results need to be improved; thus a simulation using the expanded $H$ matrix (adding PMA measured position and velocity outputs) was executed. The results from this simulation decreased the temporally averaged standard deviations for the $X$-axis and $Y$-axis rms to 3.66 $\mu$rad and 3.93 $\mu$rad, respectively. This corresponds to a 16.5 percent and 19.5 percent decrease in the $X$-axis and $Y$-axis LOS deviations, respectively. Fig. 5 illustrates the open-loop $X$-axis LOS deviation and Fig. 6 depicts the result obtained for the closed-loop $X$-axis LOS deviation. It should be noted that the controller was not activated until 0.5 s into the simulation. Note the "clamping down" of the LOS deviations after control was applied.

Space Discretization: The parameter space was discretized as described in Section V. In Tables I and II are depicted the resulting discretization weights: multiplicative values which are used to define new parameter values in the discretized parameter space.

All of the new parameter values are based from the nominal parameter values at the center of the parameter space. Table I illustrates that the system is very sensitive to variations in the undamped natural frequency; only very small increments in $\omega$ can be tolerated without causing closed-loop system instability. This sensitivity is a strong advocate for the use of moving-bank MMAC algorithms to quell oscillations introduced in the SPICE structure. Although this discretization encompasses only a 6.5% variation in $\omega$, a larger space could easily be developed using this
fine discretization level. Table II illustrates the exact opposite of Table I: the insensitivity of the system to variations in the damping ratio. This insensitivity to variations in $\zeta$ implies that only a one-dimensional space may be required yielding a MMAC algorithm that adapts to variations in $\omega$ but not to variations in $\zeta$. Thus the moving-bank MMAC results for a one-by-seven parameter space (the center row of the three-by-seven parameter space) are presented here.

Moving-Bank MMAC: This section discusses the results of the parameter identification of the moving-bank multiple model algorithm that implements the ME/I technique discussed previously. The bank move logic used is the parameter position monitoring technique. Also, it should be noted that effective parameter identification and bank movement don't take place until 1 s into the simulations depicted. For actual implementation of the controller, this delay should be removed altogether; allowing an open-loop estimator to generate good state and parameter estimates (performing only bank moves necessary to do so) for the initial 0.5 s, at which time closed-loop control is initiated (i.e., closed-loop control should not be fed back into the system until good estimation performance is achieved).

Probability lower bounds are used to avoid the “lock-out” condition discussed previously and numerical inaccuracy problems. The lower bound on the probability threshold was set to 0.20, considerably higher than used in the past [3, 4, 8], since only three elemental filter/controllers are maintained in the moving bank (with only one uncertain parameter versus two or more). The modified MMAC algorithm also incorporates an intermediate $p_k$ threshold, below which the control $u_k$ would not be included in the probability-weighted average shown in Fig. 3. This value was set to 0.25 to ensure that filters with a very low probability of being correct would not apply any (potentially destabilizing) control to the system. As long as the lower bound for preventing lock-out is less than this control threshold, algorithm performance will not be degraded by the lower bound being artificially large. Thus 0.20 is acceptable in this case, even though 0.05 is a physically more realistic lower bound.

The simulation depicted here is the case with the filter parameter value and the true parameter value set at the center of the space initially and then allowing the true parameter to jump to a second value towards the end of the admissible range. Fig. 7 is representative of the excellent parameter identification when the bank is initially centered at the true parameter value and nearly instantaneous bank movement when the true parameter value jumps. Note that the bank center is virtually indistinguishable from the parameter estimate and thus is not shown. The corresponding adaptive control is very similar to that of Fig. 6, without any significant degradation because the parameter estimation is so effective.

VII. SUMMARY

The filter discussed in this paper is based on the full-order structure system model, which is equivalent to the original full-order truth model for the structure, but with the noise shaping filters of the truth model removed, so that time-correlated noises are replaced by white noises. Order reduction of the structural model, by both modal and internally balanced model techniques, was investigated in [2], but it is not pursued here because the controller based on the full-order model doesn’t meet the stringent specifications for this application. To decrease the LOS rms deviation, either additional measurements are needed beyond the original accelerometer outputs and the additional relative position and velocity measurements of the PMAs with respect to the PMA structural connection points, or more or better actuators (as well as sensors) might be required.

The parameter space discretization results illustrate the nonlinearity of the optimum parameter space discretization. Also from the discretization, the

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Fig. 7. Typical simulation results using 1-by-7 parameter space. Initial true parameter at point 4 of Fig. 4 with jump to point 6; initial filter parameter at point 4.
variation in the $\zeta$ axis may be unnecessary due to the insensitivity of the resulting controller to this parameter. The $\omega$ parameter space only encompasses a 4.6% variation for this feasibility study; this could easily be expanded into a much larger space at the same fine level of discretization in order to encompass a wider range of parameter variations.

Using the Maximum Entropy with Identity residual covariance assumed (ME/I) estimation technique, the one-by-seven parameter space demonstrated very good true parameter identification and correspondingly excellent adaptive control. Accurate estimation of the true parameter was nearly instantaneous, even when the true parameter value jumped to a new value. The center of the moving bank also followed the parameter estimate very closely.

The results indicate that moving-bank MMAC algorithms will provide stabilizing control for the SPICE structure even with the full range of possible parameter variations. Thus, the critical shortcoming of previous nonadaptive controller designs has been overcome.

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