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Invited Paper

AN EIGENSYSTEM REALIZATION ALGORITHM USING DATA CORRELATIONS (ERA/DC) FOR MODAL PARAMETER IDENTIFICATION*

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Abstract. A modification to the Eigensystem Realization Algorithm (ERA) for modal parameter identification is presented in this paper. The ERA minimum order realization approach using singular value decomposition is combined with the philosophy of the Correlation Fit method in state space form such that response data correlations rather than actual response values are used for modal parameter identification. This new method, the ERA using data correlations (ERA/DC), reduces bias errors due to noise corruption significantly without the need for model overspecification. This method is tested using simulated five-degree-of-freedom system responses corrupted by measurement noise. It is found for this case that, when model overspecification is permitted and a minimum order solution obtained via singular value truncation, the results from the two methods are of similar quality.

Key Words—System identification, modal testing, system realization, data correlation fit, modal parameter identification.

1. Introduction

The identification of modal parameters for flexible structures from experimental data is frequently carried out using methods which operate in the time domain. Typically a curve fit to free decay response data is performed, based on a difference equation or state space mathematical model for the structure. Often, data from multiple inputs and outputs are analyzed simultaneously to allow repeated or very close natural frequencies to be identified. The resulting mathematical model yields global estimates for the modal frequencies and dampings, the complex (i.e. damped) mode shapes and the modal participation factors (i.e. initial modal amplitudes). The model may then be used for comparison with theory, for control design, etc.

A common drawback of these time domain methods is that they produce biased estimates when noise is present and the true model order used. There are various approaches used in the system identification field for reducing bias (Eykhoff, 1974). Firstly, a noise model can be used (e.g. Maximum Likelihood, Generalized Least Squares) but, because the solution is iterative and the number of unknowns is significantly increased by the noise model parameters,

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such methods have not generally been applied in modal testing. Secondly, it is possible to reduce bias by overspecification of the model order used in the solution (e.g. Repeated Least Squares) but additional spurious results are generated and need to be rejected via some criteria. This overspecification principle is used in some of the common time domain modal testing techniques. Thirdly, it is possible to eliminate or minimize the effect of the terms that cause bias using methods such as Instrumental Variables and Correlation Fit (Cooper and Wright, 1985). The Correlation Fit method, which is non-iterative and does not rely upon model overspecification, is potentially suitable for modal testing and was shown in Cooper and Wright (1985; 1986) to compare favorably to other approaches. In essence, the method is a curve fit to data correlations.

A further least squares modal testing method is the Eigensystem Realization Algorithm (ERA) (Juang and Pappa, 1985) developed at the NASA Langley Research Center. This state space method makes use of model overspecification in the initial stage in order to reduce bias. Spurious results are minimized by including the singular value decomposition in its formulation to transform the problem to one of minimum order. In practice, it appears that the process of reducing an overspecified model order by singular value truncation has beneficial effects of reducing bias.

It was pointed out in Cooper and Wright (1986) that it is possible to replace the Least Squares element in many time domain methods by the Correlation Fit approach. In this paper the ERA and Correlation Fit philosophies have been combined to produce the Eigensystem Realization Algorithm using Data Correlations (ERA/DC), to study whether the identification obtained using the ERA can be improved upon. The basic formulation of the ERA/DC is presented and results are obtained for simulated five-degree-of-freedom system response data corrupted with measurement noise. The performance of the ERA and ERA/DC is discussed in relation to the accuracy of modal damping estimates.

Nomenclature

A : state transition matrix
B : input matrix
C : output matrix
D : diagonal matrix of singular values
E_γ : block selection matrix
$H(k)$: block data matrix
I_γ : identity matrix of order γ
i, j, k, l : integer counters
m : number of inputs
O : null rectangular matrix
P : orthonormal matrix
Q : orthonormal matrix
q : initial lag value
$R(l)$: correlation matrix
r : correlation lag increment
s_j : data sample integer
t_i : data sample integer
$U(q)$: block correlation matrix
$U^\#$: pseudo-inverse of $U(q)$
$u(k)$: input vector

V_ξ, V_α : observability matrices
W_c, W_η, W_β : controllability matrices
$x(k)$: state vector
$Y(k)$: output matrix
$y(k)$: output vector
α, β : integers defining number of correlation blocks
γ : integer defining matrix dimensions
η, ξ : integers defining number of matrix blocks
l : number of outputs

2. Basic formulation

A finite-dimensional, discrete time, linear, time invariant dynamic system can be represented by the state-variable equations,

$$x(k+1) = Ax(k) + Bu(k), \tag{1}$$

$$y(k) = Cx(k), \quad k = 1,\ 2,\ \cdots, \tag{2}$$

where x is an n-dimensional state vector, u is an m-dimensional input or control vector and y is an l-dimensional output or measurement vector. The integer k is the sample indicator. The state transition matrix A characterises the dynamics of the system. For flexible structures, the matrix A is a representation of mass, stiffness and damping properties.

A special solution to the state-variable equations (1) and (2) is the impulse response function (known as the Markov parameter),

$$Y(k) = CA^{k-1}B, \quad k = 1,\ 2,\ \cdots, \tag{3}$$

where $Y(k)$ is an $l \times m$ matrix whose columns are the impulse response corresponding to the m inputs. A similar expression exists for the initial state response.

The problem of minimal system realization is as follows; given the functions $Y(k)$ from measurements, construct a set of constant matrices $[A,\ B,\ C]$ in terms of $Y(k)$ such that the identities of Eq. (3) hold and the order of A is minimum.

The Eigensystem Realization Algorithm with Data Correlations (ERA/DC) begins in a similar way to the ERA (Juang and Pappa, 1985) by defining the $(\xi+1)$ by $(\eta+1)$ block data matrix (or generalized Hankel matrix)

$$H(k-1) = \begin{bmatrix} Y(k) & Y(k+t_1) & \cdots & Y(k+t_\eta) \\ Y(s_1+k) & Y(s_1+k+t_1) & \cdots & \vdots \\ \vdots & \vdots & & \vdots \\ Y(s_\xi+k) & \cdots & \cdots & Y(s_\xi+k+t_\eta) \end{bmatrix}, \tag{4}$$

where s_j $(j=1,\ 2,\ \cdots,\ \xi)$ and t_i $(i=1,\ 2,\ \cdots,\ \eta)$ are arbitrary integers (see Juang and Pappa, 1986). Note that it is possible to write the block data matrix, and the subsequent analysis, using the more general form of Juang and Pappa

(1986). From Eqs. (3) and (4) it can be shown that

$$\left.\begin{aligned} H(k) &= V_\xi A^k W_\eta,\ V_\xi = \begin{bmatrix} C \\ CA^{s_1} \\ \vdots \\ CA^{s_\xi} \end{bmatrix} \\ \text{and } W_\eta &= [B,\ A^{t_1}B,\ \cdots,\ A^{t_\eta}B] \end{aligned}\right\}, \tag{5}$$

where V_ξ and W_η are observability and controllability matrices of dimensions $(\xi+1)l\times n$ and $n\times(\eta+1)m$ respectively. If the rank of V_ξ and W_η is n then the nth order system defined by $[A,\ B,\ C]$ is controllable and observable.

Whereas the standard ERA method proceeds from this point using the block data matrix $H(0)$, the ERA method with Data Correlations (ERA/DC) requires the definition of a square matrix of order $\gamma=(\xi+1)l$,

$$R(q) = H(q)H^T(0) = V_\xi A^q W_\eta W_\eta{}^T V_\xi{}^T = V_\xi A^q W_c, \tag{6}$$

where $W_c=W_\eta W_\eta{}^T V_\xi{}^T$. The matrix $R(q)$ consists of approximate auto correlations of outputs and cross correlations between outputs, at lag time values in the range $q\pm s_\xi$, summed over the m inputs. An $(\alpha+1)$ by $(\beta+1)$ block correlation matrix is then formed,

$$\begin{aligned} U(q) &= \begin{bmatrix} R(q) & R(q+r) & \cdots & R(q+\beta r) \\ R(q+r) & R(q+2r) & & \vdots \\ \vdots & & & \vdots \\ R(q+\alpha r) & \cdots & \cdots & R(q+(\alpha+\beta)r) \end{bmatrix} \\ &= \begin{bmatrix} V_\xi \\ V_\xi A^r \\ \vdots \\ V_\xi A^{\alpha r} \end{bmatrix} [A^q W_c,\ A^{q+r}W_c,\ \cdots,\ A^{q+\beta r}W_c] \\ &= V_\alpha W_\beta, \end{aligned} \tag{7}$$

where q is an integer chosen to avoid correlation terms which give rise to bias when noise is present, r is an integer chosen to prevent significant overlap of adjacent R blocks. The integers α and β define how many correlation lags are included in the analysis. The matrices V_α and W_β can be called block correlation observability and controllability matrices of dimension $(\alpha+1)\gamma\times n$ and $n\times(\beta+1)\gamma$ respectively.

The ERA/DC process continues with the factorization of the block correlation matrix $U(q)$ (as opposed to $H(0)$ in the ERA) using singular value decomposition so that

$$U(q) = PDQ^T, \tag{8}$$

where the columns of $P((\alpha+1)\gamma\times n)$ and $Q((\beta+1)\gamma\times n)$ are orthonormal and D is an $n\times n$ diagonal matrix containing the n singular values of $U(q)$ that are considered significant, based on some truncation criteria such as maximum signal/noise ratio (see Juang and Pappa, 1986). Note that the above factorization is approximate if noise is present because the discarded singular values are non-zero.

The pseudo-inverse $U^{\#}$ of the matrix $U(q)$, after the singular value truncation, is defined by

$$U(q)U^{\#}U(q) = U(q). \tag{9}$$

It can be shown using Eqs. (7) and (9), that

$$U^{\#} = QD^{-1}P^{T} \tag{10}$$

and also, using Eqs. (7) and (9), that

$$W_{\beta}U^{\#}V_{\alpha} = I_{n}, \tag{11}$$

where I_n is an identity matrix of order n. Define $E_{\gamma}{}^{T}=[I_{\gamma}\,0]$ and $\widetilde{E}_{\gamma}{}^{T}=[I_{\gamma}\,\widetilde{0}]$ as block selection matrices where I_{γ} is an identity matrix of order γ, and 0 and $\widetilde{0}$ are null matrices with appropriate dimensions. Following a similar approach to that presented in Juang and Pappa (1985), a minimum (or reduced) order realization of dimension n can be obtained, with the aid of Eqs. (6)–(11), from

$$\begin{aligned} R(q+j) &= E_{\gamma}{}^{T}U(q+j)\widetilde{E}_{\gamma} = E_{\gamma}{}^{T}V_{\alpha}A^{j}W_{\beta}\widetilde{E}_{\gamma} \\ &= E_{\gamma}{}^{T}V_{\alpha}[W_{\beta}U^{\#}V_{\alpha}]A^{j}\,[W_{\beta}U^{\#}V_{\alpha}]W_{\beta}\widetilde{E}_{\gamma} \\ &= E_{\gamma}{}^{T}PD^{\frac{1}{2}}[D^{-\frac{1}{2}}P^{T}V_{\alpha}A^{j}W_{\beta}QD^{\frac{1}{2}}]D^{\frac{1}{2}}Q^{T}\widetilde{E}_{\gamma} \\ &= E_{\gamma}{}^{T}PD^{\frac{1}{2}}[D^{-\frac{1}{2}}P^{T}U(q+1)QD^{-\frac{1}{2}}]^{j}D^{\frac{1}{2}}Q^{T}\widetilde{E}_{\gamma}. \end{aligned} \tag{12}$$

This is the basic formulation of the realization for the ERA/DC. Since from Eq. (6),

$$R(q+j) = V_{\xi}A^{j}(A^{q}W_{c}), \tag{13}$$

then by comparison with Eq. (12) it follows that the triple

$$[D^{-\frac{1}{2}}P^{T}U(q+1)QD^{-\frac{1}{2}},\ D^{\frac{1}{2}}Q^{T}\widetilde{E}_{\gamma},\ E_{\gamma}{}^{T}PD^{\frac{1}{2}}]$$

is a minimum realization of $[A,\ A^{q}W_{c},\ V_{\xi}]$. Now, using Eq. (5) for $H(0)$ an expression of W_{η} can be found since V_{ξ} is of rank n. The output matrix C and input matrix B can thus be identified from the first l rows of V_{ξ} and the first m columns of W_{η} respectively. Hence a realization for $[A,\ B,\ C]$ can be shown to be $[D^{-1/2}P^{T}U(q+1)QD^{-1/2},\ D^{-1/2}P^{T}\widetilde{E}_{\gamma}H(0)E_{m},\ E_{p}{}^{T}PD^{1/2}]$. This realization then leads to a transformed set of state variable equations since the two sets of matrices are related by a transformation.

The system frequencies and dampings may then be computed from the eigenvalues of the realized state transition matrix as for the ERA in Juang and Pappa (1985). The eigenvectors allow a transformation of the realization to modal space and hence the determination of the complex (or damped) mode shapes and the initial modal amplitudes (or modal participation factors). The modal amplitude coherence and modal phase collinearity (Juang and Pappa, 1985) are accuracy indicators which are calculated to indicate any spurious modes present due to imperfect singular value truncation.

It is worth pointing out that while the ERA is, in essence, a least squares fit to the impulse response measurements, the ERA/DC involves a fit to the output autocorrelations and crosscorrelations over a defined number of lag values. It is very similar to the Correlation Fit method but expressed formally as a minimum order state space realization. It may be shown that ERA is a special case of ERA/DC when $q=\alpha=\beta=0$, provided that $(\xi+1)\geq n$. This is because the ERA formulation could be written in terms of a decomposition of the correlation matrix $R(0)=H(0)H^T(0)$ instead of $H(0)$ itself.

It can also be shown that the bias terms affecting the ERA when "white" measurement noise is present can, in principle, be omitted in the ERA/DC by choosing $q\leq s_\xi+1$ (see Eq. (7)). The integer q may be determined by sensor characteristics such as covariance matrix. In order to avoid overlap of adjacent correlation terms in the block correlation matrix, it is required that $r\leq s_\xi+1$ (see Eq. (7)). The structure of the $R(q)$ matrix and hence the block correlation matrix is significantly affected by the choice of the parameter ξ. When $\xi=0$ so $s_\xi=0$, the structure is simplest, but does not necessarily yield the best answer.

3. Numerical simulation

To illustrate the behavior of the ERA and ERA/DC, results from the analysis of a simulated five-degree-of-freedom system ($n=10$) will be presented. The impulse responses are corrupted by 2[%] measurement noise (based on the rms values of signal and noise) and 30 responses with different noise samples are analyzed so that parameter means and standard deviations may be estimated; this process is sometimes referred to as a Monte Carlo Simulation (Juang and Pappa, 1986). The mean damping estimates will be presented since damping is far less easy to identify accurately than natural frequency.

The system chosen is a single input/single output (SISO) case ($l=m=1$) with distinct eigenvalues. The natural frequencies are 0.159, 0.318, 0.477, 0.636 and 0.795 [Hz] and all the modal dampings are 1[%] critical. In the model, the initial modal amplitudes and modal contributions to the output were chosen to be the same for each mode. The displacement response of the system to an impulse was generated without noise for 512 data samples at a sample interval of 0.4 [sec] and is shown in Fig. 1. The response is then corrupted by samples of random noise and the resulting data sequences analyzed by the two methods.

3.1 Results from the ERA A selection of ERA results from data with 2[%] noise is shown in Table 1 for varying dimensions of the $H(0)$ matrix. The number of columns in $H(0)$ ($(\eta+1)m$ where $m=1$) is chosen to be a measure of the number of points of the decay included in the analysis whereas the number of rows ($(\xi+1)l$ where $l=1$) is chosen to indicate the initial model order prior to any singular value truncation, i.e., a measure of model overspecification. It is clear from Table 1 that the mean damping values show significant bias when the initial model order is not overspecified (i.e. $(\xi+1)l=n=10$) and that the results deteriorate somewhat when more columns are added due to the inclusion of noisier data. When the initial model order begins to be overspecified

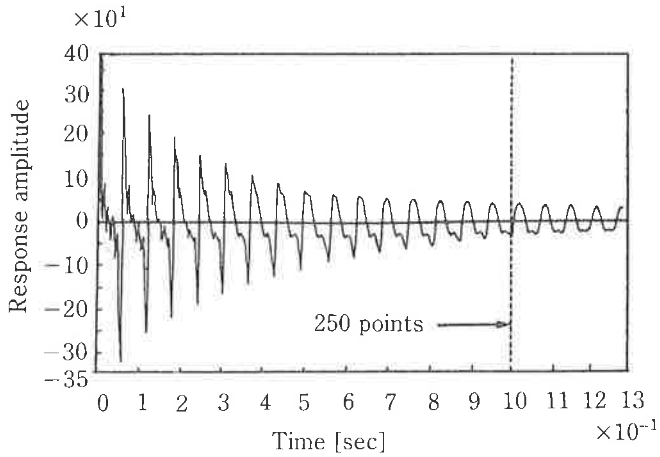

Fig. 1. Noise free impulse response.

Table 1. Mean damping results for the ERA

$H(0)$	Matrix	Mean [%] damping value				
Rows $\xi l+l$	Columns $\eta n+n$	Mode 1	Mode 2	Mode 3	Mode 4	Mode 5
10	50	10.2	12.3	9.94	3.69	1.20
	150	9.24	12.9	19.0	8.42	1.53
	250	9.08	12.5	18.5	21.8	1.83
11*	50	1.40	1.51	1.34	1.11	1.01
	150	1.50	1.86	1.69	1.27	1.03
	250	1.64	2.26	2.08	1.44	1.05
12*	50	1.01	1.03	1.03	1.02	1.00
	150	1.02	1.04	1.05	1.03	1.00
	250	1.02	1.07	1.08	1.05	1.01
15*	50	0.99	1.00	1.00	1.00	1.00
	150	1.00	1.00	1.00	1.00	1.00
	250	1.00	1.00	1.00	1.00	1.00

*Singular value truncation at order 10 carried out.

($(\xi+1)l=11,12,15$) and singular value truncation carried out, the results improve dramatically and the bias disappears by $(\xi+1)l=15$. It is well known (Eykhoff, 1974; Cooper and Wright, 1986) that overspecification of the model order reduces bias errors due to noise but additional "spurious or noise modes" are generated. These spurious modes are identified and rejected afterwards using accuracy indicators (see Juang and Pappa, 1986) in the ERA. It is seen that, in the ERA, the use of singular value decomposition for rank determination and reduced order realization largely overcome the bias without generation of spurious results. To show the similarity in results obtained with the two approaches (i.e. overspecification with and without singular value truncation),

Table 2. Mean damping results for the ERA without singular value truncation

$H(0)$	Matrix	Mean [%] damping value				
Rows $\xi l+l$	Columns $\eta n+n$	Mode 1	Mode 2	Mode 3	Mode 4	Mode 5
12	50	1.01	1.03	1.03	1.01	1.00
	150	1.02	1.04	1.05	1.02	1.00
	250	1.03	1.07	1.08	1.04	1.01

Table 2 shows similar results to those in Table 1 for $(\xi+1)l=12$ but with the realization not being of minimum order.

It should be noted when interpreting the tables of results that a mean damping value close but not equal to 1[%] may not actually be biased because of the statistical uncertainty associated with the estimate (Cooper and Wright, 1986).

While the ERA will yield results in this case of comparatively well separated modes for relatively few data points ($\eta+1$ as low as 20), in general it is important to use a significant portion of the decay (say 250 points—see Fig. 1) so as to include information on any low frequency beating due to close modes.

3.2 Results from the ERA/DC A selection of ERA/DC results from data with 2[%] noise is shown in Table 3. The $R(q)$ matrices which are the blocks in $U(q)$ were chosen to be of dimension $l\times l$ (i.e. 1×1 in this case) by making $\xi=0$; that simplifies the matrix structure considerably. The lag increment r in Eq. (7) was chosen to be 1 and the starting lag q taken as zero so no correlation terms were omitted. The approximate correlation terms were computed using $250(=\eta+1)$ data points. The integer β allowed variation of the number of correlation lag values included in the identification whereas the integer α indicated the degree of any initial model overspecification prior to singular value truncation.

Table 3 shows that when the initial model order is not overspecified (i.e. $(\alpha+1)\gamma=n=10$ where $\gamma=(\xi+1)l=1$), there is a considerable improvement in the results as the number of columns ($(\beta+1)\gamma$) in $U(0)$ increases from 10, i.e., as more correlation lag values are included. Indeed the bias is virtually eliminated without the need for overspecification and singular value truncation. This is a feature of the Correlation Fit method (Cooper and Wright, 1986), upon which the ERA/DC is based. Note that the results obtained using the 10×10 $U(0)$ matrix in ERA/DC are not the same as those from the 10×250 $H(0)$ matrix in ERA because only 1×1 $R(q)$ blocks were used; however; the results are the same for the special case when 10×10 $R(q)$ blocks are used (i.e. $(\xi+1)l=10$ or $\xi=9$ for the ERA/DC).

Although the bias can be largely removed without the need for overspecification, the results in Table 3 for $(\alpha+1)\gamma=11$, 12, 15 show that a further improvement is obtained when the solution is slightly overspecified and additional singular values truncated as for the ERA. For the same quality of results, the overspecification does not have to be as great for the ERA/DC as for the ERA. This feature may be significant for more complex and noisy data cases where the required ERA overspecification is servere.

Table 3. Mean damping results for the ERA/DC

Note $\xi = 0$; no lags omitted, $q = 0$; $(\eta+1)n = 250$

$U(0)$	Matrix	Mean [%] damping value				
Rows $\alpha\gamma+\gamma$	Columns $\beta\gamma+\gamma$	Mode 1	Mode 2	Mode 3	Mode 4	Mode 5
10	10	16.2	—	11.3	4.16	0.52
	11	1.71	—	6.18	0.29	0.94
	12	0.84	0.47	2.17	0.70	0.97
	13	0.97	1.03	1.15	1.00	1.01
	15	0.99	1.06	1.11	1.03	0.99
	20	1.06	1.06	1.08	1.02	1.00
	30	1.02	1.06	1.07	1.03	1.00
	40	1.00	1.08	1.08	1.02	1.00
11	10	1.71	—	6.18	0.29	0.94
11*	12	1.02	1.03	0.97	0.98	1.01
	20	1.00	1.00	1.00	1.00	1.00
	30	1.00	1.00	1.00	1.00	1.00
12	10	0.84	0.47	2.17	0.70	0.97
12*	12	1.03	1.08	0.96	0.94	1.01
	20	1.00	1.00	1.00	1.00	1.00
	30	1.00	1.00	1.00	1.00	1.00
15	10	0.99	1.06	1.11	1.03	0.99
15*	12	1.00	1.01	1.00	1.00	1.00
	20	1.00	1.00	1.00	1.00	1.00
	30	1.00	1.00	1.00	1.00	1.00

*Singular value truncation at order 10 carried out.

From theoretical considerations of the ERA/DC, it was expected that a choice of $q>0$ would have omitted the zero lag autocorrelation, which is corrupted by the mean square of the measurement noise, from the analysis and thus reduced the bias. However, the behavior of the ERA/DC results for increasing q was not clear cut and the definite benefit seen using the equivalent parameter in the correlation Fit method for a two degree of freedom data case (Cooper and Wright, 1986) was not obtained. This feature of the ERA/DC is probably connected with the nature of the autocorrelation of the underlying signal in that significant low lag information is omitted as q is increased. Further investigation is required.

3.3 Further comments In order to compare the relative ability of the ERA and ERA/DC to determine the order of the system from overspecified matrices, the normalized singular values were obtained for a single noisy response. The ERA values for $H(0)$ (15×250) were [1.0, 0.95, 0.74, 0.69, 0.59, 0.55, 0.49, 0.46, 0.43, 0.38, 0.0087, 0.0085, 0.0081, 0.0077, 0.0071] and the square roots of the ERA/DC singular values for $U(0)$ (15×20) were [1, 0.96, 0.73, 0.70, 0.58, 0.56, 0.49, 0.46, 0.42, 0.40, 0.0297, 0.0752, 0.138, 0.0130, 0.0109]. The square root is necessary for easy and fair comparison. In this case the ERA results show a more definite "drop" beyond the 10th singular value. The

ERA/DC "drop" varies according to the number of lags used and the block size of the $R(q)$ matrix. The inclusion of higher lag correlation data means that the effective signal/noise ratio for the $U(0)$ matrix decreases.

The results shown in this paper indicate that both the ERA and ERA/DC yield equally good results for this data case provided that initial model overspecification and singular value truncation are used. This is perhaps not surprising upon study of the methods since the ERA can be thought of as using a square correlation matrix $H(0)H^T(0)$ of order at least n. However the ERA/DC uses, in general, a rectangular correlation matrix with at least n rows but an arbitrary number of columns (which need not usually be much larger than n), the detailed structure of the matrix depending upon the $R(q)$ block size ($\gamma \times \gamma$). Thus, when the ERA uses an overspecified initial model order, additional correlation information is included (rather than adding extra lags in the ERA/DC) and this information is retained during the transformation of the matrices to a reduced order.

The relative performance of the two methods needs further consideration, particularly for data where modes are close, the model order may be high and multiple inputs and outputs used. Also, the effect of the block size of the $R(q)$ matrix in the ERA/DC needs evaluation.

4. Conclusion

A modification of the ERA which uses data correlations rather than response values has been presented. This method (ERA/DC) has been compared to the ERA for simulated five-degree-of-freedom data corrupted by measurement noise. The results indicate the ERA/DC can reduce bias without model overspecification. However, when overspecification is permitted and singular value decomposition used to obtain a minimum order realization, both methods give equally good results for the data used. The ERA/DC needs further evaluation to see if it can provide any improvement over the ERA when applied to more complex data.

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