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Automated data interpretation for practical bridge identification

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Abstract. Vibration-based structural identification has become an important tool for structural health monitoring and safety evaluation. However, various kinds of uncertainties (e.g., observation noise) involved in the field test data obstruct automation system identification for accurate and fast structural safety evaluation. A practical way including a data preprocessing procedure and a vector backward auto-regressive (VBAR) method has been investigated for practical bridge identification. The data preprocessing procedure serves to improve the data quality, which consists of multi-level uncertainty mitigation techniques. The VBAR method provides a determinative way to automatically distinguish structural modes from extraneous modes arising from uncertainty. Ambient test data of a cantilever beam is investigated to demonstrate how the proposed method automatically interprets vibration data for structural modal estimation. Especially, structural identification of a truss bridge using field test data is also performed to study the effectiveness of the proposed method for real bridge identification.

Keywords: structural identification; ambient vibration; automate; uncertainty; signal processing

1. Introduction

Structural Identification (St-Id) of a number of bridges through ambient or controlled vibration tests have been investigated in the literature (ASCE 2012, Samali *et al.* 2010, Fukuda *et al.* 2010, Pakzad and Fenves 2011, Loh and Liu 2013). These case studies significantly improve the St-Id technology for bridge safety monitoring. However, uncertainty involved in field test data still poses major challenges to automated St-Id, and hinder a more routine adoption of St-Id approaches in support of infrastructure maintenance and management.

Various unavoidable uncertainties come from every aspect of ambient or controlled vibration tests. For instance, environmental conditions (humidity and temperature) affect the sensitivity of deployed experimental hardware, and structural components like bearing may enter into nonlinear range thus bring uncertainty into the St-Id process (Moon and Aktan 2006, Zhang *et al.* 2009, Yang *et al.* 2012). These uncertainties with epistemic and aleatory mechanism not only affect the

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accuracy of St-Id results, but produce extraneous modes in structural modal analyses (Magalhaes *et al.* 2009, Ali and Okabayashi 2011). Structural modes and spurious modes are simultaneously produced in the data interpretation stage, associating with structural property and uncertainty, respectively. They are difficult to distinguish thus they are manually separated in most traditional methods, such as the peak picking, autoregressive with moving average (ARMA), and complex mode indicator function (CMIF). A few methods have been developed in the literature for automated structure mode selection. Three indicators: extended modal amplitude coherence, modal phase collinearity, and consistent mode indicator (CMI), were proposed to select structure modes specifically for use with the eigensystem realization algorithm. Pappa *et al.* (1998) proposed a recursive procedure using a threshold concept to filter out unfeasible modal identification results, in which the threshold was CMI < 50%, damping ratio >10%, or the frequency within 1% of edges of analysis bandwidth. Pakzad and Fenves (2009) used the ARMA method to perform statistical analysis of the vibration modes of the Golden Gate Bridge, and the threshold similar to that of Pappa *et al*. (1998) was employed to delete extra, nonphysical modes. Heylen *et al.* (1997) used the stabilization diagram to eliminate spurious numerical poles from the ARMA model. Magalhaes *et al.* (2009) proposed a hierarchical clustering algorithm used together with the SSI method for automatic mode identification.

This article focuses on the following questions to cope with uncertainty from the data interpretation aspect for practical structural identification: (a) how to mitigate the uncertainty and improve the data quality for accurate St-Id; (b) how to automatically identify structure modes with little or no human intervention for efficient St-Id. To deal with the first problem, a multi-level data pre-processing procedure is developed for uncertainty mitigating and data quality improving. Visual inspection, time window selection, digital filtering, data averaging, cross-correlation function or random decrement signature construction, exponential windowing, and data reliability evaluation are effectively integrated for uncertainty mitigation. To deal with the second problem, a vector backward autoregressive (VBAR) method is applied for automated structural mode selection. Its uniqueness lies on that it provides a determined way to automatically separate structural models from spurious ones. Theoretic analyses will be presented to explain how the VBAR method automatically separate structural modes from extraneous ones. System identification of a laboratory cantilever beam and a long-span truss bridge using the proposed method will be presented to illustrate its effectiveness for practical bridge identification.

2. Automated data interpration method

2.1 Data pre-processing strategy for uncertainty mitigation

Ambient vibration testing provides a convenient way for structural dynamic characterizing because it utilizes service live loads (wind, traffic, etc.) already acting on the structure as excitations. However, special attentions are required to reduce the noise level for subsequent St-Id. Without raw data cleaning, the accuracy and reliability of identified structural parameters may be greatly affected. A multi-level data pre-processing procedure including the following steps is developed to improve the data quality (Fig. 1): First, acceleration records are inspected to identify any malfunctioning sensors. If an acceleration time series contained large spikes or bias, the channel is tagged and disregarded from further processing and analysis. Second, a time window selection algorithm is executed to remove windows with pronounced noise. This involves

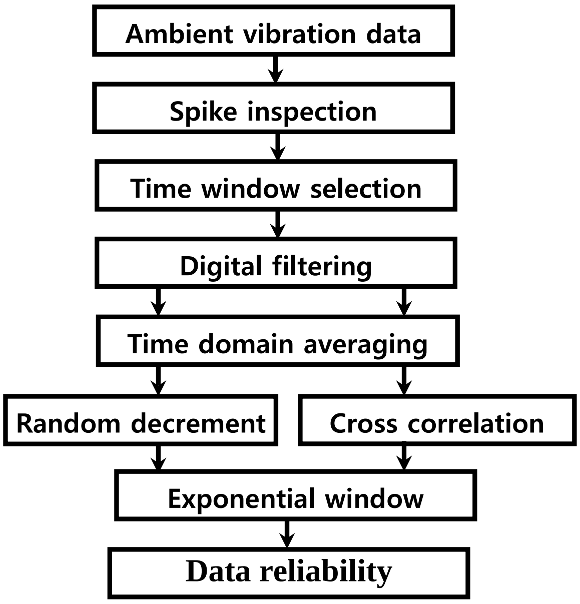


Fig. 1 Data pre-processing flowchart

segmenting the entire data record into a series of time windows, and computing the mean and standard deviation of the acceleration amplitude for each time window. If the standard deviation of a given window is found to be much larger, that section of data is tagged and removed. After the time window selection analysis is completed for the entire data record, a digital Butterworth band pass filter with certain cut-off frequencies is designed to reduce the low and high frequency components. Following that, data averaging is performed to reduce random noise. Data averaging in the time domain is executed by dividing the total data time history into a number of windows having the same length and averaging these segments. It is a simple but very effective way to improve the accuracy of the St-Id results. Data averaging can also be performed in the frequency domain.

After the initial data cleaning presented above, the Random Decrement (RD) technique or the Cross-Correlation analysis is employed to transform ambient vibration data into a free decay response of the structure that is measured (Brownjohn *et al.* 2009, Ku *et al.* 2007). After free-decay data are estimated from the RD technique or the Cross-Correlation analysis, exponential window is used to artificially force the response data to decay to zero at the end of measurement thus minimizing leakage. As the last step of the data pre-processing, a data relevance and reliability evaluation procedure is necessary to check whether the cleaned data have adequate quality for subsequent data post-processing. For instance, two acceleration segments from the same location but at different time window may be processed by using the presented procedure for uncertainty mitigation then to check whether they produce similar spectra curves.

2.2 Vector backward AR nodel for automatic data interpretation

The vector backward AR (VBAR) method is applied to interpret the pre-processed data for structural modal identification. Equations below illustrate the theoretical basis how this method automatically distinguishes structural modes from spurious modes. Structural responses of an n degrees of freedom system with random excitations can be presented by a complex exponential model

$$y(j) = \sum_{k=1}^{n} b_k \exp(s_{kj} \Delta t), \quad j = 1,2,..., N \tag{1}$$

$$s_k = \alpha_k + 2\pi f_k i \tag{2}$$

where, $y(j)$ = a sequence of structural response, b_k = amplitude coefficient, N = sample number, n = term of the model, s_k = the complex frequency, f_k = frequency in Hz, α_k = damping factor, $i = \sqrt{-1}$ and Δt = sample interval in seconds. To solve unknown parameters b_k and s_k, the Prony method was developed to transform the nonlinear problem to a set of linear constant-coefficient difference equations. It utilizes a polynomial $P(z)$ having the $z_k = \exp(s_k)$ as its roots

$$P(z) = \prod_{k=1}^{n} (z - z_k) \tag{3}$$

The products of Eq. (3) can be expanded as the summation

$$P(z) = \sum_{j=0}^{n} a_k z^{-j} \tag{4}$$

with coefficients α_k such that α_0 = 1. The following equation is derived by using Eqs. (1) and (4)

$$\begin{Bmatrix} y(n+1) \\ y(n+2) \\ \vdots \\ y(N) \end{Bmatrix} = -\begin{bmatrix} y(N) & y(n-1) & \vdots & y(1) \\ y(n+1) & y(n) & \cdots & y(2) \\ \vdots & \vdots & \ddots & \vdots \\ y(N-1) & y(n-2) & \cdots & y(N-n) \end{bmatrix} \begin{Bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{Bmatrix} \tag{5}$$

It is seen that Eq. (5) is same to the traditional forward Auto-Regressive (AR) model. It demonstrates that the polynomial coefficients a_k, k = 1, …, n, form a linear predictive relationship among the time samples. Therefore, it can be solved from Eq. (5) by using the least square method. Subsequently, roots z_k of the polynomial in Eq. (3) are solved, and structural frequency and damping factor can be extracted from the polynomial root. The ith mode shape, φ_i, can be derived from the following equation

$$P(z_i)\, \varphi_i = 0 \tag{6}$$

$P(z_i)$ in Eq. (6) is calculated by substituting the solved z_i into Eq. (3). In Eq. (6) the Due to uncertainty involved in the test data, the identified frequency and damping factors from the above equations are generally inaccurate. Several ways have been developed to improve the accuracy of the least square Prony method. Using high prediction order is one of those methods. Eq. (5) is rewritten as the following equation by defining the high prediction order as q

$$Y^f A^f = 0 \tag{7}$$

where $Y^f = \begin{bmatrix} y(q+1) & y(q) & \dots & y(1) \\ y(q+2) & y(q+1) & \cdots & y(2) \\ \vdots & \vdots & \ddots & \vdots \\ y(N) & y(N-1) & \cdots & y(N-q) \end{bmatrix}$, and $A^f = \begin{Bmatrix} a_1^f \\ a_2^f \\ \vdots \\ a_q^f \end{Bmatrix}$.

The identification results using high order AR model as shown in Eq. (7) are more accurate, but the arising problem is how to distinguish the extraneous roots due to the uncertainty from all numerical roots of the Prony character polynomial. To solve this problem, a backward predictor by rearranging the sequence in a backward manner can be derived from Eq (7)

$$Y^b A^b = 0 \tag{8}$$

where $Y^b = \begin{bmatrix} y(1) & y(2) & \cdots & y(q+1) \\ y(2) & y(3) & \cdots & y(q+2) \\ \vdots & \vdots & \ddots & \vdots \\ y(N-q) & y(N-q+1) & \cdots & y(N) \end{bmatrix}$, and $A^b = \begin{Bmatrix} a_1^b \\ a_2^b \\ \vdots \\ a_q^b \end{Bmatrix}$.

It is seen that Eqs. (7) and (8) are the forward and backward AR models with high orders. The characteristic polynomials $P^f(z) = \sum_{j=0}^{q} a_k^f z^{-j}$, and $P^b(z) = \sum_{j=0}^{q} a_k^b z^{-j}$ with coefficient matrix A^f and A^b have q polynomial roots. n of the q roots consisting of structural modal information are called system roots. The other $(q - n)$ roots arising due to the uncertainties involved in the experiment and St-Id processes are called extraneous roots. Then the question arises that how to separate the system roots from the extraneous roots for structural identification. The location of the polynomial roots for both the forward and backward linear predictors are summarized below in order to find a way for system and extraneous root separation:

(a) ***System roots of the forward predictor, Eq. (7).*** It is proved (Chu 2003) that if the coefficient matrix vector A satisfies $Y^f A^f = 0$, and if q satisfies the inequality $n \le q \le (N - n)$, then $P^f(z)$ with polynomial matrix A^f has n of its q roots at $z_k^f = \exp(s_k^f)$, $k = 1, 2, \ldots, q$. Chu (2003) proved that these n system roots z_k^f from the forward predictor fall inside the unit circle of the z-plane.

(b) ***System roots of the backward predictor, Eq. (8).*** If the coefficient matrix vector A satisfies $Y^b A^b = 0$, and if q satisfies the inequality $n \le q \le (N - n)$, then $P^b(z)$ with polynomial matrix A^b has n of its q roots at $z_k^b = \exp((-s_k^f)^*)$, $k = 1, 2, \ldots, q$, where symbol $(\ )^*$ denotes complex conjugate. It is obvious that $|\exp(s_k^f)| = 1/|\exp((-s_k^f)^*)|$. Therefore, the n system roots z_k^b from the backward predictor fall outside the unit circle.

(c) ***Extraneous roots of both the forward and backward predictors.*** Chu (2003) proved that the q order $(n \le q \le (N - n))$ polynomials $P^f(z)$ and $P^b(z)$, have the same $(q - n)$ extraneous roots, because the statistics of a stationary random process do not change whether process is time reversed. These extraneous roots locate inside of the unit circle.

In brief, both the system and extraneous roots for the forward linear predictor, Eq. (7), fall inside of the unit circle. For the backward predictor, the signal roots locate outside of the unit circle, while the extraneous roots locate inside of the unit circle. Therefore, the results from the backward predictor provide a determinative way to automatically distinguish the n system roots from the $(q - n)$ extraneous roots. This feature of the backward AR model awards an automated modal identification way, which is much more efficient than the traditional forward AR method.

Fig. 2 Cantilever beam ambient test layout

3. Cantilever beam ambient test for modal identification

Vibration test data of a cantilever beam are investigated to illustrate how the developed method for automatic data interpretation. The test specimen is a steel beam with a thin-walled rectangular tube section 76 × 38 × 0.32mm (Fig. 2). The length of the beam between the tip and support location is 2.98 m. The test specimen is oriented on a steel pedestal so that it would bend about its weak axis under vertical loads (Pan 2007). The physical structure is excited by manual tapping input distributing over the superstructure, which can be seen as a narrow band random excitation. Six accelerometers labeled from acc1 to acc6 are installed on the cantilever beam with equal intervals to observe structural responses. The first accelerometer was put on the fix end of the beam, whose measurement is only be used to check the boundary condition. Therefore, the beam is seen as a 5-DOF structure and the responses observed from the other five sensors are processed for structural identification. The sampling of the ambient test data is 0.00125 second, and the total duration of the observed time series is 10 minutes. The measured acceleration at the support of the beam (acc1) is very weak due to the approximating ideally fixed boundary. Therefore, the tested beam is assumed to be an ideally cantilever beam, and the observed data at the boundary is not used in structural modal identification.

The developed data pre-processing techniques are performed to clean the raw data, among which the RD technique is utilized to transform the test data to free decay time series. Fig. 3(a) plots observed acceleration time series at the 3rd channel, and Fig. 3(b) illustrates the corresponding free-decay data estimated by the RD technique by taking the 5th channel measurement as the reference. In the RD technique, the trigger level is selected as the 1.5 times the standard deviation of the signal. The block size, namely the number of samples consisted in an averaged time segment, is selected as 8192 in this study.

After data pre-processing, the vector backward AR (VBAR) model is applied to identify the cantilever beam modal parameters. Here the $AR(p, q)$ model with p = 5 and q = 6 is selected to simulate structural dynamic responses, where p is the measurement channel number, and q is the AR order. Full measurement case is first studied, where p equals the number of structural DOF. The least squares method is used to identify AR coefficient matrix in Eq. (7), then $p \times q$ numerical roots are calculated from Eq. (3). As presented in Section 2, the system roots of the backward AR model fall outside of the unit circle, while the extraneous roots locate inside of the unit circle. This is proved in Fig. 4(a) that 10 structure roots and 20 extraneous roots fell outside and inside of the unite cycle, respectively. These 10 structure root are complex conjugate, thus structural

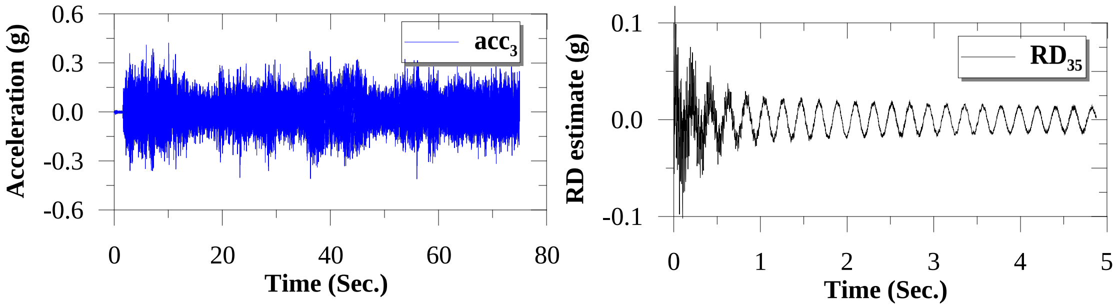
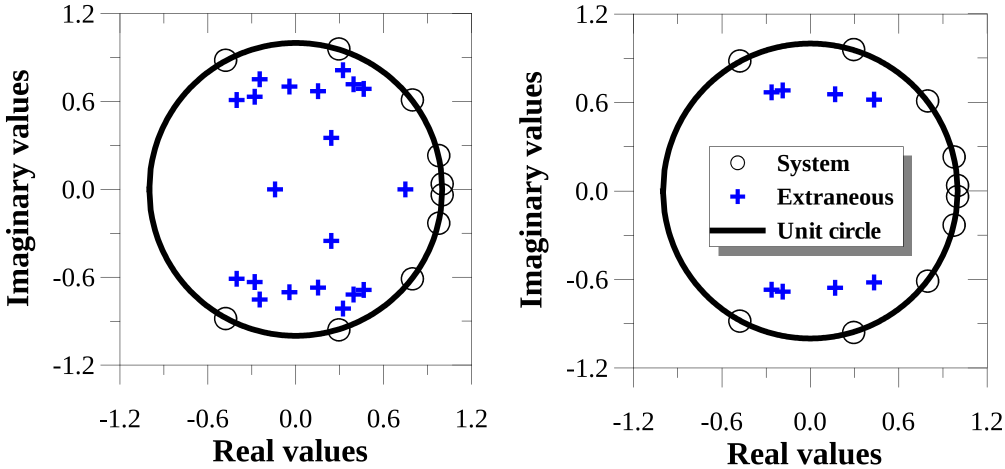


Fig. 3 Data pre-processing by the RD technique



(a) Full measurement (b) Incomplete measurement

Fig. 4 Locations of the system and extraneous roots from the backward AR models

frequencies, damping ratio, and mode shapes in 5 modes are extracted from them. This case clearly illustrates that the *n* system roots consisting of structural modal parameters are automatically separated from the extraneous modes by using the backward AR model, unlike that the selection has to be manually performed in the common forward AR model.

Structural identification using incomplete measurements of this cantilever beam is also studied because generally only a few measurements are available from the ambient test of large scale civil infrastructures due to limited sensors. Instead of full measurements used above, only three channel measurements at the 1^{st}, 3^{rd}, and 5^{th} nodes are used to check whether the developed method can produce accurate St-Id results when the measurements are incomplete. The same data pre-processing and identifying procedure are performed by using a backward *AR*(3, 6) model, in which p = 3 is the measurement channel number, and q = 6 is the AR order the same as that in the full measurement case. All $p \times q$ = 18 numerical roots are plotted in Fig. 4(b). It is clear that the 10 structure roots are successfully separated from the others in the incomplete measurement case. Fig. 5 plots the identified frequencies and damping ratios in all 5 modes from both the full and incomplete measurement cases. Identified mode shapes from both cases are also almost same, which are not shown here for brevity.

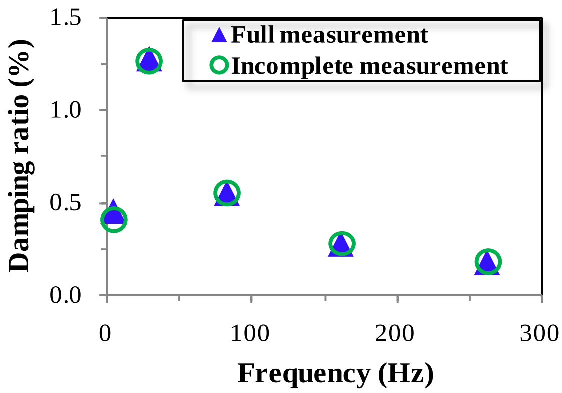


Fig. 5 St-Id results from both full and incomplete

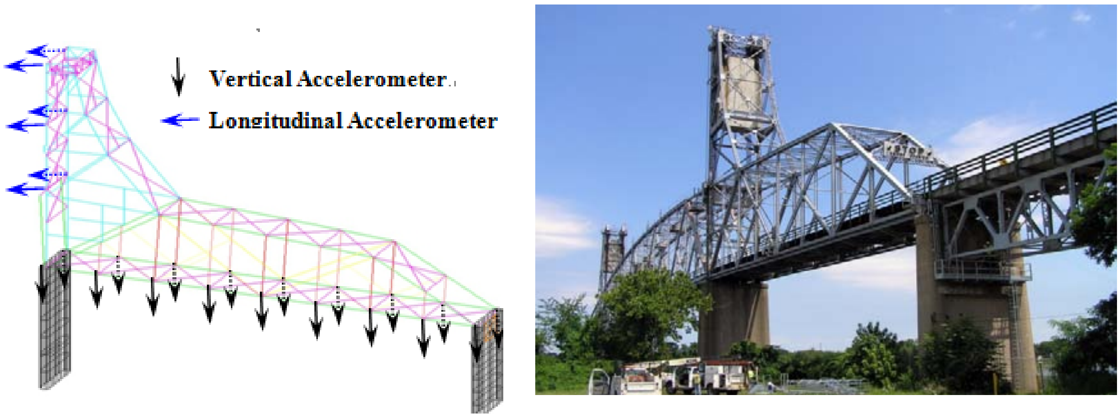
Table 1 Correlation analysis of the St-Id results

Identified Modes	CMIF		Backward AR (CORR)		Backward AR (RD)	
	Frequency (Hz)	Damping ratio (%)	Frequency (Hz)	Damping ratio (%)	Frequency (Hz)	Damping ratio (%)
Tower-L1, Span-V1	2.090	4.720	2.105	5.261	2.120	5.934
Tower-L2, Span-V1	4.033	1.083	4.024	1.365	4.032	1.468
Tower-L2, Span-V2	5.714	1.617	5.761	1.604	5.774	1.778
Tower-T2, Span-T1	6.341	0.847	6.361	0.589	6.346	0.493
Tower-T1, Span-T1	--	--	6.763	0.328	6.754	0.353
Tower-T2, Span-T2a	7.948	0.523	7.948	0.446	7.950	0.464
Tower-L2, Span-V3	8.028	3.491	8.369	1.611	8.381	2.130
Tower-L2, Span-V4	9.617	1.057	9.680	0.944	9.732	1.198
Tower-T2, Span-T2b	10.343	0.449	10.320	0.553	10.339	0.589
Tower-T2, Span-V5	10.712	1.702	10.611	0.752	10.569	1.220
Tower-T2, Span-V6	--	--	11.560	0.784	11.506	1.109
Tower-T2, Span-T3	12.727	1.108	12.889	0.617	12.920	0.463
Tower-L3, Span-T4	--	--	--	--	14.101	0.333
Tower-L2, Span-T5	--	--	--	--	16.029	0.114

-- denotes no identified parameters in that mode

4. Auto data interpretation for ST-ID of a truss bridge

Structural identification using field test data of real life bridges faces much more challenges than that using numerical or laboratory experiment data. Ambient vibration test data of a long span truss bridge is studied to validate the proposed method for real life bridge identification. This truss bridge has a total length from abutment to abutment of 701m (Fig. 6(a)). It is 6.1m wide and carries two lanes of vehicular traffic across the river. Other than load rating, live load monitoring, local impact testing, and truck load test, ambient vibration test has been performed on this aged bridge as a part of safety monitoring strategies. Test data of the south tower span with instrument setup as shown in Fig. 6(b) are used in this part, in which a total of 24 channels of the measured data consisting of the vertical response of the span and the longitudinal response of the tower (Fig. 6(b)) are included.



(a) Sensor layout on the tower span (b) Photo

Fig. 6 The investigated bridge

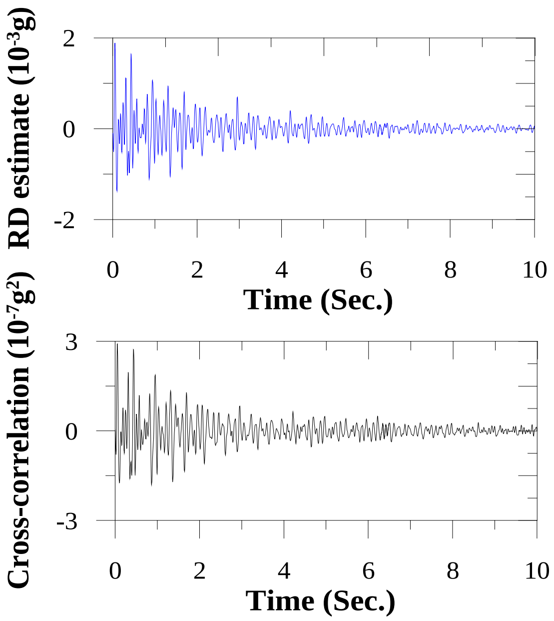


Fig. 7 RD estimate and cross-correlation function of an acceleration time series

The developed data pre-processing procedure (Fig. 1) is first executed for raw data cleaning. A digital Butterworth band pass filter with cut-off frequencies at 0.1 and 20 Hz is designed to reduce the low and high frequency components embedded in the data. Both the RD technique and the cross-correlation analysis are performed to transform the ambient vibration response to the free-decay time series (Fig. 7), respectively. The free decay data from the RD technique and the cross correlation analysis are post-processed by the backward AR model, respectively (referenced as backward AR (RD) and backward AR (CORR) methods in the following part). The backward *AR*(24, 20) model, with 24 measurement channels and the order of 20, is used to simulate structure responses, thereby a total of 20 × 24 numerical roots are calculated. In the backward AR(RD) process, 36 system roots are outside the unit circle, while 184 extraneous ones fall inside the unit circle (Fig. 8(a)). Similarly, 44 system roots and 176 extraneous roots locate outside and inside of the unit circle respectively in the backward AR(CORR) process (Fig. 8(b)), respectively. Even though the selected structural roots from the backward AR (RD) and backward AR (CORR) methods are not exactly same, a number of extraneous modes have been automatically selected out in both methods by using the backward AR model. Following this automatic data interpretation procedure, structure frequencies, damping ratios, and mode shapes are easily calculated from the separated system roots. Table 1 shows the identified frequencies and damping ratios in the first 14 modes from these two methods, and Fig. 9 plots the corresponding mode shapes identified by the backward AR (RD) method. The symbols in the figure denote the tower and span mode type and mode number. For instance, "L1, V1" in the first figure denotes the tower has a first mode in the longitudinal direction and the span has a first mode in the vertical direction. To verify the reliability of the St-Id results, correlation analysis is performed by comparing the identified parameters from the backward AR (CORR) and backward AR (RD) methods. Identified frequencies and damping ratio from the Complex Mode Indicator Function (CMIF) method are also provided in Table 1 for comparison. The modal assurance criterion (MAC) plot comparing the identified mode shapes from the backward AR (RD) and backward AR (CORR) methods is shown in Fig. 10(a). Similarly Fig. 10(b) illustrates the MAC values from the backward AR (RD) and the CMIF identification. It is seen that the frequencies, damping ratios and modal shapes from the backward AR (CORR) and backward AR (RD) methods are comparable, and both of them identified more structural modes than the CMIF method. This real life bridge identification example illustrates that the data processed by the proposed pre-processing procedure has good quality and the VBAR method automatically distinguish system roots from spurious ones thus carry out automated data interpretation for structural identification. The following additional findings are also made during the St-Id of this real bridge: (a) Data pre-processing is a critical step in the proposed St-Id procedure. If the raw data are not well cleaned, some structure roots may be wrongly classified as extraneous ones in the backward AR method. (b) Using more reference data in the RD method and the Cross-Correlation analysis improves the quality of the pre-processed

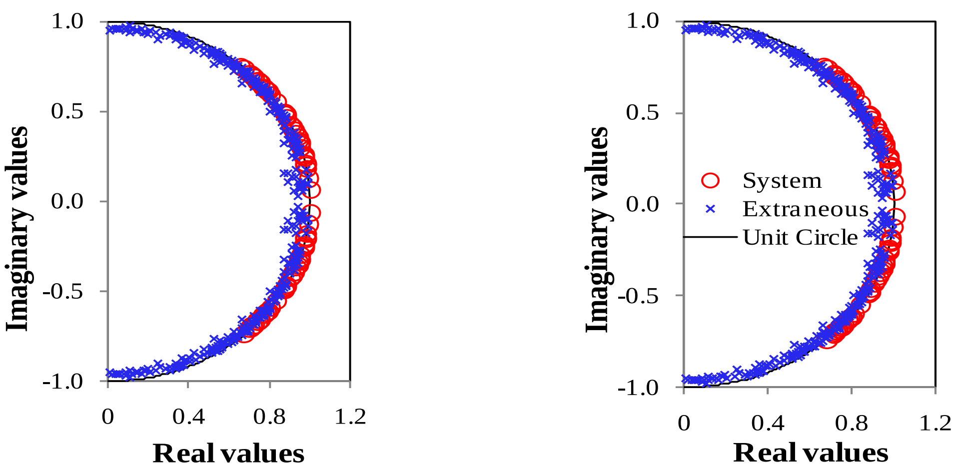


Fig. 8 Numerical modes from the backward AR (RD) and the backward AR (CORR) methods

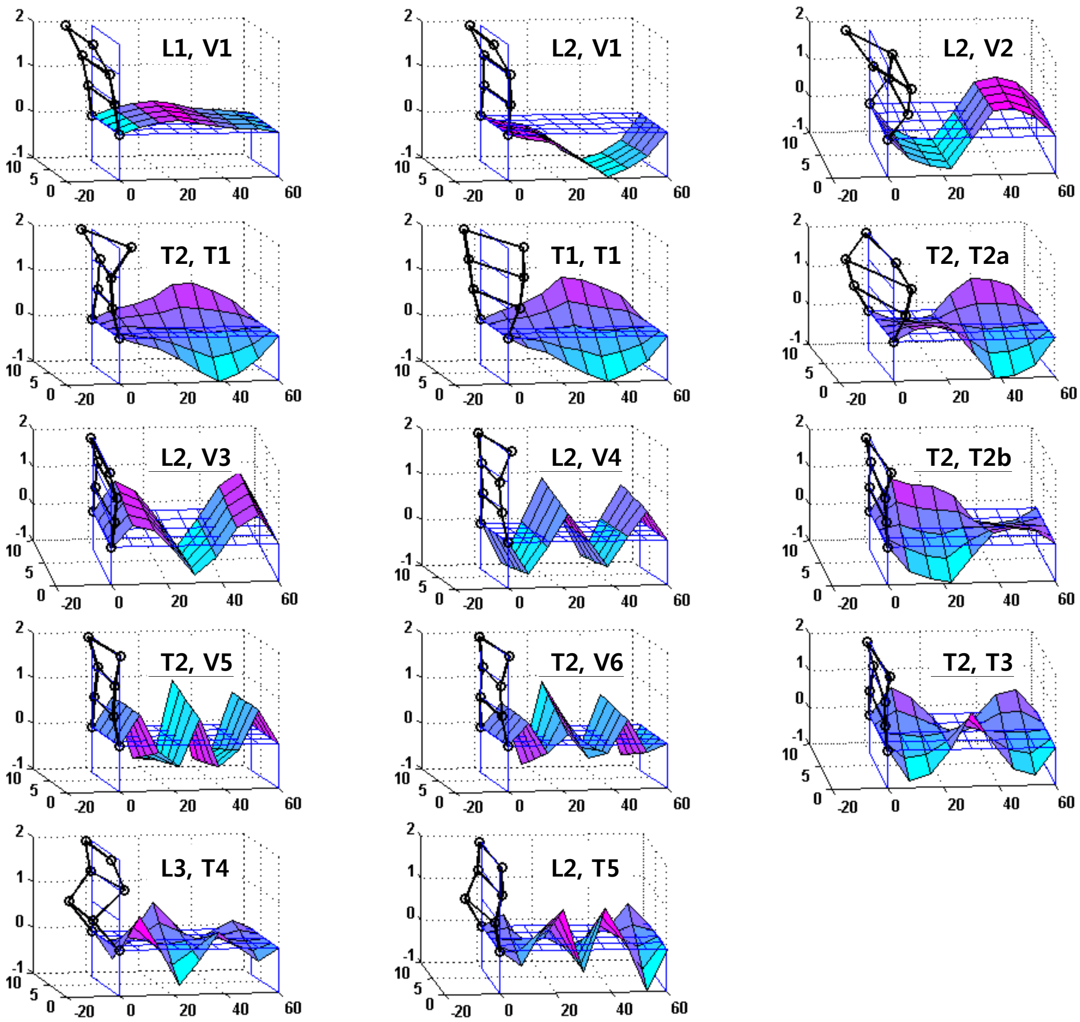
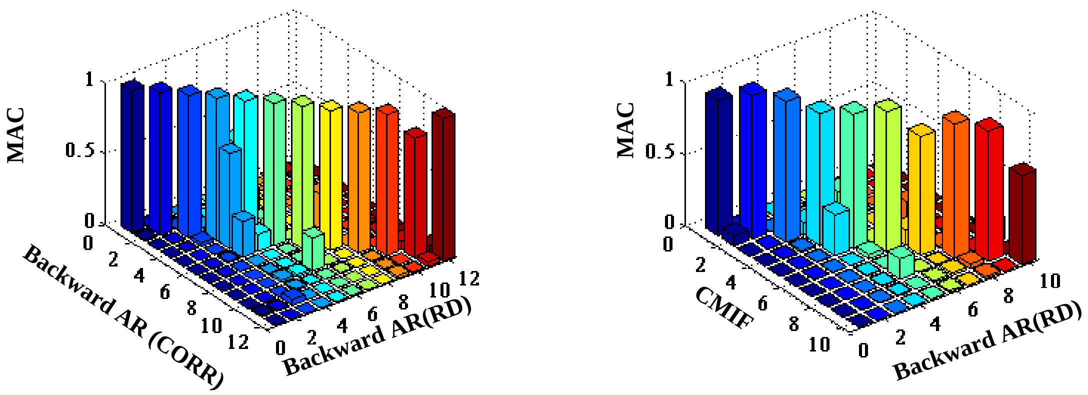


Fig. 9 Identified Mode shapes from the backward AR (RD) methods



(a) backward AR (RD) and backward AR (CORR) method (b) backward AR (RD) and CMIF method

Fig. 10 Mode shape comparison

data. Both the RD and the Cross-Correlation methods can be performed by using a single or multiple time series as the reference. System identification based on single-reference data may produce bad results, especially when sensors are located on uncoupled components and the observed acceleration responses have no much relevance.

5. Conclusions

An automatic data interpretation way integrating a multi-level pre-processing procedure and a VBAR based post-processing method has been proposed for practical bridge identification. Based on the results of this study the following conclusions are drawn:

• A multi-level data preprocessing procedure has been proposed for raw data quality improving. The quality of the cleaned data from the pre-processing procedure greatly influenced the efficiency of the proposed data post-processing method for modal identification, and the way to automatically perform the pre-processing strategies is challenging.

• A vector backward AR (VBAR) model has been applied for automatic bridge identification. Its uniqueness is that it provides a determinate way to separate structure modes from extraneous modes arising from uncertainty.

• Ambient vibration test data of a cantilever beam test has been used to demonstrate how the proposed method automatically separate structure modes from extraneous modes. Both full measurement and incomplete measurement cases were investigated.

• The proposed method has been performed for modal identification of a long span truss bridge through ambient vibration test. The identified results show that the proposed method was able to automatically distinguish structural modes from spurious even for real structure identification. A total of 14 modes of the tower span of the studied bridge were identified from the developed method, and they are comparable with the identified results from the traditional CMIF method.

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