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Research paper

SSI improved algorithm based on zero phase filtering technology for structural parameter identification in civil engineering

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Abstract: Early damage detection and reinforcement of civil engineering structures are crucial. To ensure timely maintenance in the later stage, the civil structure is subjected to modal parameter identification. In vibration signal recognition, traditional stochastic subspace vibration signal recognition has modal omissions. Previous studies have shown that using singular value decomposition can suppress signals with lower energy. Therefore, zero-phase filtering technology is used to improve the random subspace identification method. Singular value decomposition is used for structural parameter analysis and noise suppression. The zero-phase filtering technology is combined to solve the low-energy signal loss. Therefore, an improved stochastic subspace identification method for civil engineering structural parameter identification is proposed. This study validates the proposed method through experiments, analyzes the corresponding design parameters and experimental data results, and verifies the advantages and feasibility of this method. According to the research results, there were multiple peaks within 0–10 Hz under environmental effects, with 3.15 Hz and 4.84 Hz corresponding to the first two modes of the system. Under the action of vehicle load, two peaks were displayed around 3.15 Hz and 4.84 Hz, with two clearly stable axes. The system order was determined to be $N = 4$ through the stability diagram. Under relevant amplitude conditions, the estimated damping ratio of the two test points in the second mode was always equal to 0.55%. It can effectively analyze the natural frequency and damping ratio in civil engineering structures, laying the foundation for damage detection in civil engineering structures.

Keywords: zero phase filtering technology; stochastic subspace identification; civil engineering; structural parameters; modal recognition

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1. Introduction

The identification of modal parameters of civil engineering structures is an important task that aims to provide an important basis for structural safety assessment and preventive maintenance work by analysing vibration characteristics [1]. Modal parameters are the basic information for analysing the dynamic characteristics of structures and have wide applications in structural health monitoring, damage identification and wind design. By quantitatively measuring and analysing these parameters, structural health can be effectively assessed and appropriate repair measures can be taken [2]. However, the identification of structural parameters in civil engineering requires the acquisition of vibration signals for analysis. Therefore, singular value decomposition (SVD) is used to solve the structural matrix and suppress the noise. Stochastic subspace identification (SSI) is a commonly used modal identification method for civil engineering structures, but it cannot effectively solve the noise problem in vibration signals. Therefore, an improved SSI method based on zero-phase filtering technique is proposed in this paper to improve the efficiency of structure detection. It improves the structural dynamics theory and modal parameter identification method to a certain extent, and lays the foundation for the damage detection of civil engineering structures. This research will improve the structural dynamics theory and modal parameter identification method to a certain extent.

This research is divided into four parts. The first part elaborates on the research background, significance, and prospects of modal parameter identification. The second part focuses on the SSI method based on zero phase filtering technology designed in this article, which is also the focus and innovation of this study. The third part elaborates on the experimental results based on the algorithm designed in the second part. The fourth part summarizes the experimental conclusions, elaborates on the flaws and the directions that need to be further explored in the future.

2. Related works

In civil engineering structures, structural vibration periods, damping ratios and other parameters are calculated for civil engineering to assess the safety and reliability of the structure. This is one of the current research hotspots in this field. Luo et al. proposed an autonomous mode estimation algorithm to automatically eliminate false modes and quantify uncertainty. The proposed model discrimination index was more effective than the traditional indicator threshold in identifying true and false modes [3]. The measurement of pulse wave propagation speed and resonance frequency is related to structural design. The joint interpretation of frequency and velocity changes needs to better understand the health status of the structure. Skodowska et al. explained the common seismic changes in pulse wave velocity and fundamental frequency using the Timoshenko beam building model. This study indicated that there were changes in two parameters before and after earthquakes [4]. Stochastic subspace algorithm is one of the most widely used structural identification techniques, usually involving modal parameter estimation. Some scattered modes in the stability diagram may be identified as stable results, which may have adverse effects on the structural mode identification. Therefore, Zhou et al. proposed an improved Monte

Carlo based stochastic subspace algorithm containing stable graphs. The data showed that this method had good performance in distinguishing poles representing physical patterns from poles representing scattered patterns, which accurately and robustly estimated structural modal parameters [5]. To develop a robust method for identifying output modes, Li et al. introduced a new model. The Second Order Blind Identification (SOBI) was combined with Covariance-driven Stochastic Subspace Identification (COV-SSI). The results indicated that the proposed method accurately and reliably identified relevant modal parameters. The modal discrimination steps related to the proposed method were clearer and more intuitive than the stable graph [6].

Many proposed structural damage detection methods are unable to accurately identify the location and severity of damage. Ghahremani proposed an accurate damage identification method based on stiffness matrix decomposition. The accuracy decreased when complex incentives were applied to the structure. The proposed method was more accurate than the other methods in diagnosing the severity of damage [7]. Operational Modal Analysis (OMA) is one of the most important processes in structural health monitoring. Santos et al. proposed a universal automatic OMA strategy. This strategy effectively estimated modal parameters in complex structures. The dissimilarity and k-medoid based on modal guarantee criteria were the best set and clustering method for dissimilarity measurement [8]. Intelligent buildings are a key component of such smart cities. Automated structural health monitoring is crucial. Do proposed an automated damage detection method for shear type building structures. This method effectively eliminated the mass effect and accurately determined the location and severity of structural damage [9]. Under external loads such as seismic excitation, structural damage assessment requires appropriate data analysis to interpret measurement data and identify structural states. Huang et al. applied a recursive subspace recognition algorithm to study time-varying dynamic characteristics. The results indicated that the rows in the data Hankel matrix had a significant impact on the identification of time-varying fundamental frequencies in the structure [10].

Structural parameter identification in civil engineering includes modal estimation, stochastic subspace algorithm, second order blind identification, and OMA. However, there are still few measures to solve the noise problem of vibration signals in civil structures. A new method based on zero phase filtering technology is proposed to study structural parameters and dynamic characteristics, providing a technical basis for damage detection of civil building structures.

3. Structural parameter identification in civil engineering based on improved SSI

This chapter first constructs a SSI civil structural parameter identification method, which uses SVD for data processing to suppress noise and improve accuracy. Secondly, in order to improve the efficiency of parameter identification, an improved method based on zero phase filtering technology is proposed.

3.1. Identification and analysis of modal parameters in civil engineering structures based on SSI

In civil engineering, modal parameter identification is an important method for determining the dynamic and modal characteristics of structures. The frequency response function is the best method for analyzing modes [11, 12]. In this study, the frequency response function of a single degree of freedom system was defined to obtain a multi degree of freedom system as shown in Fig. 1.

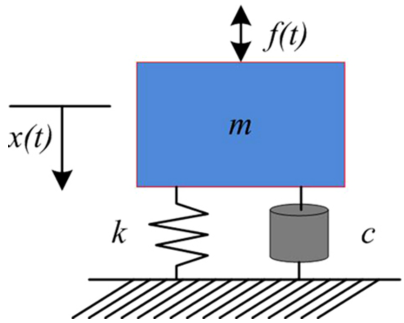


Fig. 1. Simplified diagram of a single-degree-of-freedom system

In Fig. 1, $f(t)$ and $x(t)$ represent the damping force and vibration velocity experienced by a SDOF viscous damping system. t represents time, c represents the damping coefficient. k represents a constant.

The frequency response function is the tangent of the transfer function. The impulse response function and the frequency response function are Fourier transforms of each other. The SSI method is used to identify civil engineering structures [13]. It works by looking at the output of the system and is good at identifying modal responses even when there is noise. SVD is an important matrix decomposition technique that decomposes moments into the product of three matrices [14, 15]. A Hankel matrix is a matrix in which the elements on each sub-diagonal are equal. The output block Hankel matrix is shown in equation (3.1).

$$H = \frac{1}{\sqrt{j}} \begin{pmatrix} y_0 & y_1 & \cdots & y_{j-1} \\ \cdots & \cdots & \cdots & \cdots \\ y_{i-2} & y_{i-1} & \cdots & y_{i+j-3} \\ y_{i-1} & y_i & \cdots & y_{i+j-2} \\ \hline y_i & y_{i+1} & \cdots & y_{i+j-1} \\ y_{i+1} & y_{i+2} & \cdots & y_{i+j} \\ \cdots & \cdots & \cdots & \cdots \\ y_{2i-1} & y_{2i} & \cdots & y_{2i+j-2} \end{pmatrix}^{\text{def}} = \left(\frac{Y_{0li-1}}{Y_{il2i-1}}\right)^{\text{def}} = \left(\frac{Y_p}{Y_f}\right) \tag{3.1}$$

In equation (3.1), the Hankel matrix is composed of $2i$ rows and j columns. Y represents an element. p represents the past. f represents the future. Then the Toeplitz matrix of the relevant system is constructed, which is composed of the covariance matrix of the output data.

Considering the limited output data obtained during the actual measurement process, the final definition and composition form are shown in equation (3.2).

$$\begin{cases} Z_i = \dfrac{1}{j} \displaystyle\sum_{k=0}^{j-1} y_{k+i}, y_k^T \\ T_{l|i} = Y_f Y_p^T = \begin{pmatrix} Z_i & Z_{i-1} & \dots & Z_1 \\ Z_{i+1} & Z_i & \dots & Z_2 \\ \dots & \dots & \dots & \dots \\ Z_{2i-1} & Z_{2i-2} & \dots & Z_i \end{pmatrix} \end{cases} \tag{3.2}$$

In equation (3.2), Z_i represents the mathematical model definition of SSI. Γ_i represents the matrix composition form. $T_{l|i}$ denotes the Toeplitz matrix. The Toeplitz matrix is constructed to improve the speed and efficiency of the modal parameter identification algorithm. This is done by simplifying the Hankel matrix while maintaining the original information. The number of rows and columns is changed from $2li \times j$ to $li \times li$. The system matrix is then solved. To observe and control the system, an SVD decomposition of the Toeplitz matrix is performed to reflect the rank of the matrix over non-zero singular values. The matrix expression is shown in equation (3.3).

$$\begin{cases} \Gamma_i = (C \quad CA \ \dots \ CA^{i-1}) \\ \Delta_i^d = (A^{i-1}G \ \dots \ AG \quad G) \end{cases} \tag{3.3}$$

In equation (3.3), Γ_i represents the observable matrix. Δ_i^d represents the inverse controllable matrix. C represents the result obtained by taking the first l rows of the non singular matrix T_i. G represents the matrix obtained by taking the first l rows of the matrix Δ_i^d. A represents the system state matrix, which is expressed as equation (3.4).

$$A = S_1^{-1/2} U_1^T T_{2/i+1} V_1 S_1^{-1/2} \tag{3.4}$$

In equation (3.4), U and V are orthogonal matrices. S is a diagonal matrix. The system modal parameter identification is carried out, which includes damping ratio, modal shape, and natural frequency. It can be calculated through the eigenvalue decomposition of the state matrix Λ. The eigenvalue decomposition of the state matrix Λ, and the relationship between the continuous time system state matrix and the DTS can be expressed as equation (3.5).

$$\begin{cases} A = \Phi\Lambda\Phi^{-1} \\ A = e^{A_c \Delta t} \\ A = e^{\Phi_c \Lambda_c \Phi_c^{-1} \Delta t} = \Phi_c e^{\Lambda_c \Delta_t} \Phi_c^{-4} \end{cases} \tag{3.5}$$

In equation (3.5), Λ represents a diagonal matrix containing complex eigenvalues. Φ represents a matrix composed of eigenvectors. A_c represents the state matrix of DTS. A represents the continuous time system state matrix. Δt represents the sampling time interval. The relationship between the eigenvalues of the continuous time system and DTS can be obtained. The relationship between the eigenvalues of the DTS matrix A_c, circular frequency, and damping ratio is shown in equation (3.6).

$$\begin{cases} \lambda_m = e^{\lambda_{ci} \Delta t} \\ \lambda_{cm} \bar{\lambda}_{cm} = -\xi_m \omega_m \pm j\omega_m \sqrt{1 - \xi_m^2} \end{cases} \tag{3.6}$$

In equation (3.6), λ_m represents the eigenvalues of the DTS matrix A_c. ω_m represents the circular frequency. ξ_m represents the damping ratio. The vibration frequency and damping ration are shown in equation (3.7).

$$\left\{\begin{array}{l} \lambda_{cm}\bar{\lambda}_{cm} = a_m \pm j b_m \\ f_m = \dfrac{\sqrt{a_m^2 + b_m^2}}{2\pi} \\ \xi_m = \dfrac{-a_m}{\sqrt{a_m^2 + b_m^2}} \end{array}\right. \tag{3.7}$$

In equation (3.7), a_m and b_m represent the real and imaginary parts of the m-th modal eigenvalue of the system. f_m represents the vibration frequency. The modal vibration mode is shown in equation (3.8).

$$\Psi = C\Phi \tag{3.8}$$

The system correlation matrix is solved similarly for both COV-SSI and DATA-SSI. It is important to accurately solve the system order at each stage of system identification for SSI to effectively identify the system [16]. Common methods include the singular value jump method, which is affected by noise. This paper proposes a stability diagram method based on SSI to identify the uncertainty limit. The method assumes the system has multiple orders. The true modes are more stable than false modes caused by noise [17].

3.2. Improved SSI method based on zero phase filtering technology

SSI is an effective method for modal identification in power systems, but modal components in power structure systems are not uniformly distributed, so there is noise in the data [18]. This study used SVD to process the data, but it also suppresses the relatively low energy modal response components. Therefore, this study proposes a zero-phase filtering based on the dynamic properties of civil engineering structures to analyse a structural system for parameter identification. In the dynamic analysis, the dynamic structural system is described as equation (3.9).

$$\left\{\begin{array}{l} MU''(t) + CU'(t) + KU(t) = \widetilde{x}(t) \\ X'(t) = A_c X(t) + B_c u(t) \\ A_c = \begin{pmatrix} 0 & I_{n_2} \\ -M^{-1}K & -M^{-1}C_2 \end{pmatrix} \quad B_c = \begin{pmatrix} 0 \\ M^{-1}B_2 \end{pmatrix} \end{array}\right. \tag{3.9}$$

In equation (3.9), $X(t)$ refers to the state vector. $A_c = \begin{bmatrix} 0 & I \\ -M^{-1}K & -M^{-1}C \end{bmatrix}$ and $B_c = \begin{bmatrix} 0 \\ M^{-1} \end{bmatrix}$ refer to the state matrix and input matrix. $X'(t)$ represents the first order differential equation form after transforming $\widetilde{x}(t)$, which is convenient for analysis. K represents a constant. C represents an observable matrix. In practice, the power system response is generally measured through acceleration sensors, velocity sensors, or displacement sensors. Therefore, the corresponding observation equation and state vector are displayed in equation (3.10).

$$\begin{cases} y(t) = C_n U''(t) + C_v U'(t) + C_d U(t) \\ y(t) = C_c X(t) + D_c u(t) \end{cases} \tag{3.10}$$

The equation (3.10) constitutes the time state space model, which is converted into the corresponding discrete form as shown in equation (3.11).

$$\begin{cases} x_{k+1} = Ax_k + Bu_k \\ y_k = Cx_k + Du_k \end{cases} \tag{3.11}$$

In equation (3.11), $x_k = x(k\Delta t)$ represents the DTS variable. $A = \exp(A_c \Delta t)$ represents the DTS matrix. B represents the discrete input matrix. The response signal of a structural system inevitably contains noise components. Generally, the uncertainty components of the system include process noise and measurement noise. Therefore, equation (3.12) is changed to a discrete state space model, such as equation (3.13).

$$\begin{cases} x_{k+1} = Ax_k + Bu_k + w_k \\ y_k = Cx_k + Du_k + v_k \end{cases} \tag{3.12}$$

In equation (3.12), w_k represents process noise. v_k represents measurement noise. Finally, continuous time eigenvalues are obtained as shown in equation (3.13).

$$\lambda_c = \ln \lambda / \Delta t = -\xi\omega \pm j\omega\sqrt{1-\xi} \tag{3.13}$$

In equation (3.13), ξ represents the damping ratio. ω represents the natural frequency. λ_c represents the duration characteristic value. λ represents the discrete time eigenvalue. Δt refers to the sampling time interval. Then the modal parameters are determined, as shown in equation (3.14).

$$f = \frac{\sqrt{a^2+b^2}}{2\pi}, \quad \xi = \frac{-a}{\sqrt{\sqrt{a^2+b^2}}} \tag{3.14}$$

In equation (3.14), a and b refer to the real and imaginary parts of the eigenvalue. An improved method based on zero phase filtering technology is proposed. The algorithm process is shown in Fig. 2.

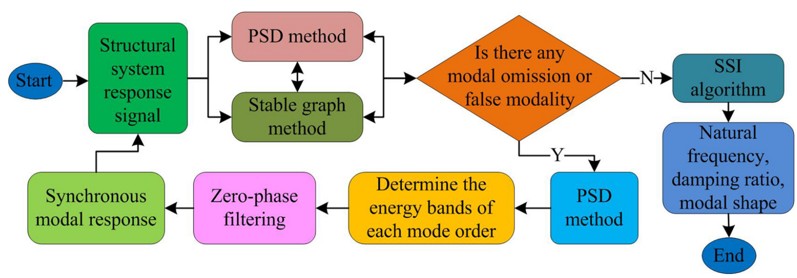


Fig. 2. An improved modal parameter identification method based on zero phase filtering technology

The improved algorithm has the same energy levels as the SSI method, weakening the effect of SVD on low-energy modal components. Each energy level has a set bandwidth and the signals are split and filtered separately. They are then combined to smoothen the signals at different frequencies. Fig. 3 shows how forward and reverse filtering works.

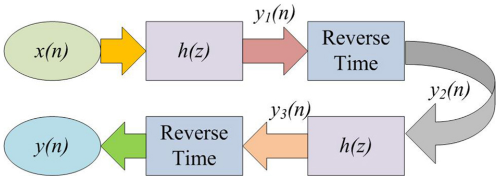


Fig. 3. FRR zero phase filtering process

In Fig. 3, $h(n)$ represents the unit pulse response sequence. $h(z)$ represents the transformed filter sequence. $x(n)$ represents the input sequence. $y_1(n)$ represents the sequence filtered by filter $h(z)$. $y_2(n)$ represents the flipped output sequence. $y_3(n)$ represents the sequence after reverse filtering. $y(n)$ represents the final sequence after reversing $y_3(n)$, which is precise and has zero phase distortion, as shown in equation (3.15).

$$Y\left(e^{j\omega}\right) = X\left(e^{j\omega}\right) |H\left(e^{j\omega}\right)|^2 \tag{3.15}$$

In equation (3.15), $Y\left(e^{j\omega}\right)$ represents the output signal. $X\left(e^{j\omega}\right)$ represents the input signal.

4. Experimental verification of identification method for structural parameters in civil engineering

4.1. Experimental data preparation and design

A bridge project was chosen for the experiment. Acceleration sensors were used to test the vibration signals of the arch bridge. The arch bridge was monitored using the acceleration sensor. Fig. 4 shows the time course of the acquisition points and a zoomed-in view of the local acceleration signals. D1 to D5 show the locations of the sensors. To test the algorithm, we use a very tall building. The building has 3 underground floors and 45 above-ground floors, with a total height of 234.3 m. Acceleration sensors are installed.

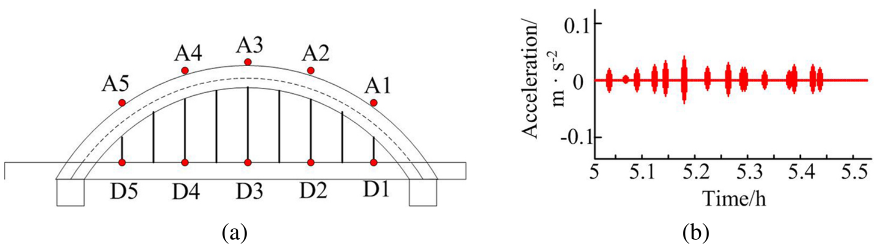


Fig. 4. Collection points and acceleration signal time history: (a) Layout diagram of acceleration sensors, (b) Time history of bridge measured acceleration signal

4.2. Statistical analysis of identification experiment results

Different methods of signal estimation were used in the experiment. Fig. 5 shows the power density spectral analysis of the acceleration signals from some of the sensors.

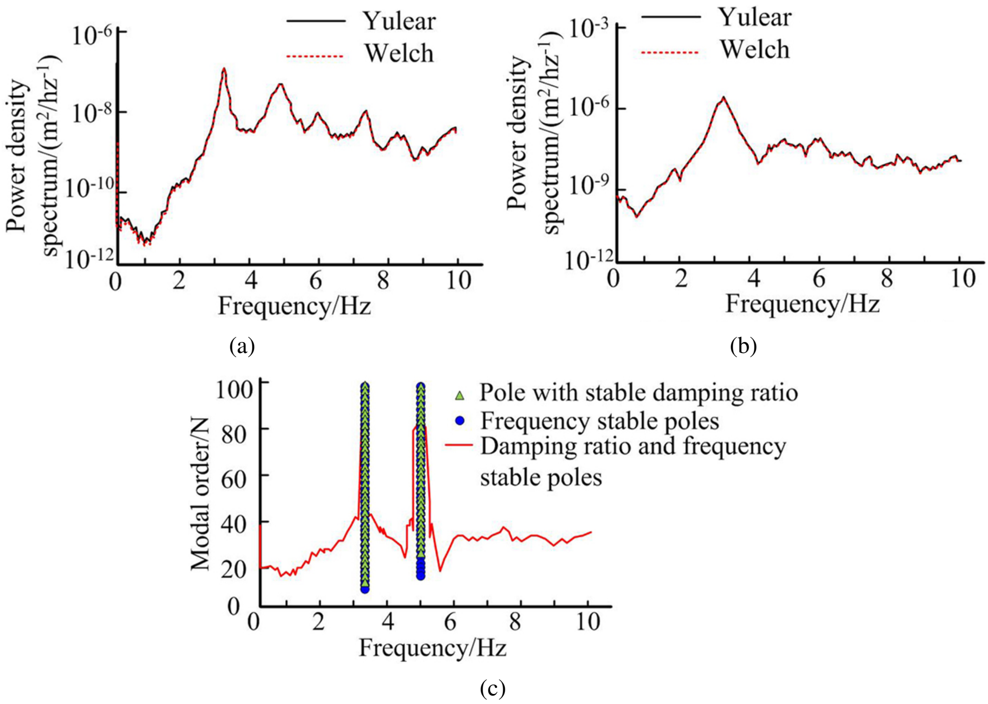


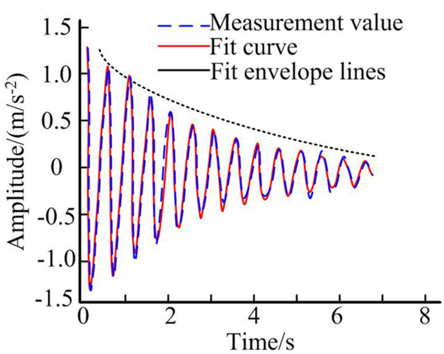
Fig. 5. Natural frequency identification of civil engineering bridge structures in two cases and stability map after SSI method processing: (a) Environmental spectrum analysis results, (b) Analysis results of vehicle load spectrum, (c) Stability map obtained by SSI

Figure 5(a) shows multiple peaks in the range of 0–10 Hz for ambient conditions. 3.15 Hz and 4.84 Hz are the first two system modes. 0.5 hours of data was used to analyse the vibration of the arch bridge during vehicle loading. The signal is a vibration signal. Fig. 5(c) shows the stability map after SSI processing. Fig. 5(b) shows two peaks around 3.15 Hz and 4.84 Hz under vehicle load. Fig. 5(c) shows two stabilisation axes around 3.15 Hz and 4.84 Hz. The system order is $N = 4$. Random Decrement Technique (RDT) is a vibration analysis method. It is used to calculate the free response of structures like space shuttles. Table 1 shows the results of identifying bridge modal parameters under different working conditions, including the RDT and SSI methods. The two modal identification methods gave similar results for frequency. The damping ratio results were different. Different methods require different lengths and qualities of data. If you don't get reliable RDS with the RDT method, you need more samples.

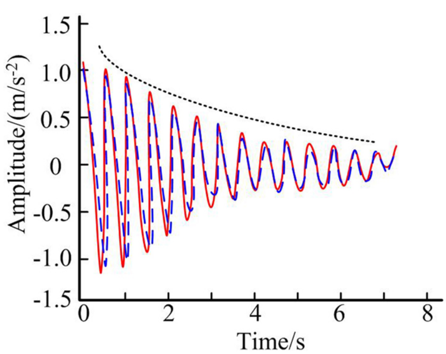
Table 1. Identification results of bridge modal parameters under different working conditions

Modal order			**First vertical mode**		**Second vertical mode**	
			Environmental load	**Vehicle load**	**Environmental load**	**Vehicle load**
Bridge deck (A)	Frequency	RDT	3.12	3.12	4.84	4.81
		SSI	3.11	3.13	4.82	4.87
		Diff. (%)	0.36	–0.36	1.11	–1.47
	Damping ratio	RDT	1.05	0.88	1.37	1.62
		SSI	1.09	0.91	1.36	1.21
		Diff. (%)	–2.99	–8.41	0.75	27.4
Arch rib (D)	Frequency	RDT	3.12	3.11	4.82	4.77
		SSI	3.11	3.11	4.88	4.82
		Diff. (%)	0.34	0.01	–1.62	–1.51
	Damping ratio	RDT	0.67	0.84	1.19	0.97
		SSI	0.63	0.81	1.15	0.99
		Diff. (%)	8.84	8.46	4.28	–4.29

Figure 6 shows the damping ratio estimated by the RDT method. The random attenuation signal is similar to the free attenuation curve of a damped SDOF system. The damping ratio of the two test points in the second mode was always 0.55%. This shows that the system takes a long time to settle in this mode. This may also be related to the material, structure and connection method. More analysis needed.



(a)



(b)

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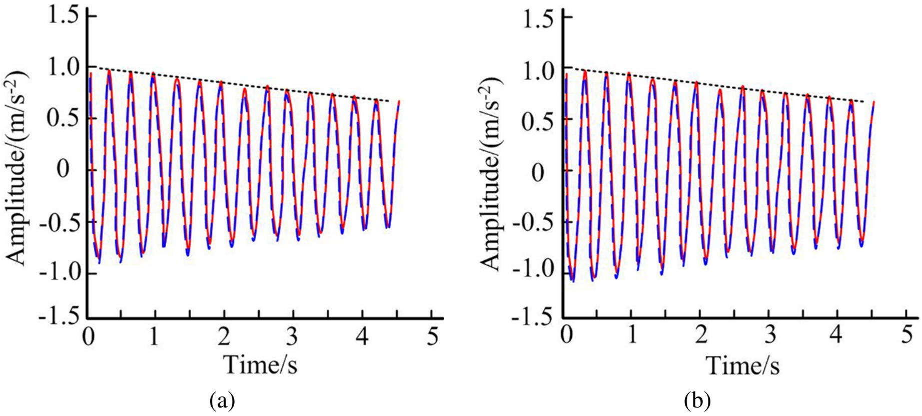

Fig. 6. Damping ratio estimated by RDT method: (a) Frequency 2.12 Hz, damping ratio 2.88%, order 50, (b) Frequency 2.051 Hz, damping ratio 2.60%, order 68, (c) Frequency 312 Hz, damping ratio 0.55%, order 1192, (d) Frequency 3.12 Hz, damping ratio 0.55%, order 1192

The experiment looks at some high-rise buildings. Each channel's acceleration data is analysed. Fig. 7 shows some results. The frequency point amplitude in the acceleration power density spectrum curve was sharp and obvious. The spectrum curve shows good consistency at 0.191 Hz, 0.716 Hz, and 1.457 Hz. We can reliably identify the natural frequency. The unimproved and improved SSI are used to analyse the system. The stability diagram is drawn. Fig. 7(a) shows false stable axes and modal omissions. Fig. 7(b) shows a clear stable axis at the natural frequency, so the order $N = 10$ of the civil engineering structural system was determined.

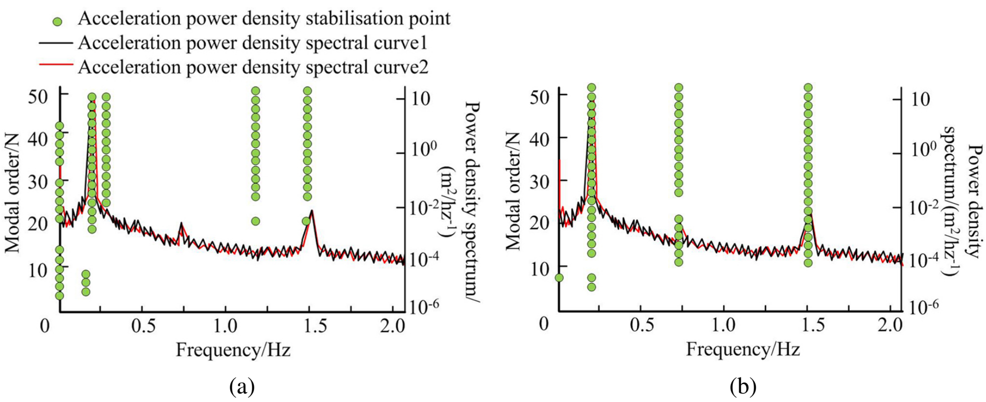

Fig. 7. PSD analysis results of acceleration data in various channels of high-rise buildings: (a) Stable graph obtained from unimproved SSI, (b) Stable graph obtained from improved SSI

The improved SSI method is applied for modal parameter identification. The relevant results are displayed in Table 2. The modal frequency information obtained by the improved SSI method was in good agreement with the results corresponding to the spectral estimation method. For the damping ratio, the second mode results obtained by the two methods were in good agreement. The traditional SSI method couldn't identify the second mode. The modal shapes obtained by the improved SSI method and RMS method are compared. The MAC value between the two results was close to 100%, indicating that the identification results of the modal shapes were consistent.

Table 2. Comparison of modal parameter results for high-rise buildings obtained by improved SSI method and other methods

Modal order		**East-west orientation**		**North-south orientation**	
		First order	**Second order**	**First order**	**Second order**
Natural frequency (Hz)	PSD	0.184	0.682	0.188	0.689
	SSI	0.188	0.711	0.187	0.691
	Relative error (%)	–1.62	–3.97	0.541	–0.154
Damping ratio (%)	PSD	0.721	0.511	0.668	0.478
	SSI	0.475	0.532	0.561	0.443
	Relative error (%)	34.2	–3.94	15.4	6.37

5. Conclusions

Modal parameter identification is a key research area in civil engineering. It brings together mechanics, mathematics and computer technology. It is important for building civil engineering structures. Modal parameter identification uses existing data to help optimise the design of civil engineering structures. A new method based on zero phase filtering technology was proposed. It was then used to identify structural parameters in civil engineering to improve efficiency. The estimated damping ratio at the two test points in the second mode was always 0.55%. The first modal results differed significantly between the improved SSI and RDT methods. However, the second-order modal results were in good agreement with the modal shape identification results. The frequency point amplitude in the acceleration power density spectrum curve was sharp and obvious. The spectral curves showed good consistency around 0.191 Hz, 0.716 Hz, and 1.457 Hz. The natural frequency can be reliably identified. The study shows that this method can be used to analyse civil engineering structures. The study only looks at some parameters. Other monitoring methods will also be used. We will explore how structural parameter changes affect physical mechanisms and other fields.

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References

[1] Y.L. He, Z.H. Yuan, and J.Z. Huang, "Random vector functional linknetwork with subspace-based local connections", *AppliedIntelligence*, vol. 53, no. 2, pp. 1567–1585, 2023, doi: 10.1007/s10489-022-03404-8.

[2] M. Damadipour, R. Tarinejad, and M.H. Aminfar, "Weighted transmissibility-based operational modal analysis for identification of structures using seismic responses", *Iranian Journal of Science andTechnology – Transactions of Civil Engineering*, vol. 45, no. 1, pp. 43–59, 2020, doi: 10.1007/s40996-020-00509-3.

[3] Y. Luo, Y. Liu, J. Han, and J. Liu, "Automatic modal parameters identification and uncertainty quantification based on block-bootstrap and multi-stage clustering under ambient excitation", *Journal of Low Frequency Noise, Vibration and Active Control*, vol. 41, no. 2, pp. 551–565, 2022, doi: 10.1177/14613484211051844.

[4] A.M. Skodowska, C. Holden, P. Guéguen, J. Finnegan, and G. Sidwell, "Structural change detection applying long-term seismic interferometry by deconvolution method to a modern civil engineering structure (New Zealand)", *Bulletin of Earthquake Engineering*, vol. 19, no. 9, pp. 3551–3569, 2021, doi: 10.1007/s10518-021-01110-3.

[5] K. Zhou, Q.S. Li, and X.L. Han, "Modal identification of civil structures via stochastic subspace algorithm with monte carlo-based stabilization diagram", *Journal of Structural Engineering*, vol. 148, no. 6, 2022.

[6] J. Li, T. Bao, and C. Ventura, "A robust methodology for output-only modal identification of civil engineering structures", *Engineering Structures*, vol. 270, no. 11, pp. 443–462, 2022, doi: 10.1016/j.engstruct.2022.114764.

[7] B. Ghahremani and M. Bitaraf, "Damage assessment using stiffness matrix decomposition and output-only modal identification", *Iranian Journal of Science and Technology – Transactions of Civil Engineering*, vol. 45, no. 3, pp. 1623–1631, 2021, doi: 10.1007/s40996-021-00607-w.

[8] J. Santos, C. Crémona, and P. Silveira, "Automatic operational modal analysis of complex civil infrastructures", *Structural Engineering International*, vol. 30, no. 3, pp. 365–380, 2020, doi: 10.1080/10168664.2020.1749012.

[9] N.T. Do and M. Gul, "Structural damage detection under multiple stiffness and mass changes using time series models and adaptive zerophase component analysis", *Structural Control and Health Monitoring*, vol. 27, no. 8, 2020, doi: 10.1002/stc.2577.

[10] S.K. Huang, J.D. Chen, K.J. Loh, and C.H. Loh, "Discussion of user-defined parameters for recursive subspace identification: Application to seismic response of building structures", *Earthquake Engineering & Structural Dynamics*, vol. 49, no. 15, pp. 1738–1757, 2020, doi: 10.1002/eqe.3327.

[11] S. Deegalla, K. Walgama, P. Papapetrou, and H. Boström, "Random subspace and random projection nearest neighbor ensembles for high dimensional data", *Expert Systems with Applications*, vol. 191, no. 4, art. no. 116078, 2022, doi: 10.1016/j.eswa.2021.116078.

[12] A. Kaveh, P. Rahmani, and A.D. Eslamlou, "Guided water strider algorithm for structural damage detection using incomplete modal data", *Iranian Journal of Science and Technology – Transactions of Civil Engineering*, vol. 46, no. 2, pp. 771–788, 2022, doi: 10.1007/s40996-020-00552-0.

[13] S. Jahan, A. Mojtahedi, S. Mohammadyzadeh, and H. Hokmabady, "A fuzzy krill herd approach for structural health monitoring of bridges using operational modal analysis", *Iranian Journal of Science and Technology – Transactions of Civil Engineering*, vol. 45, no. 2, pp. 1139–1157, 2021, doi: 10.1007/s40996-020-00475-w.

[14] L. Zhi, F. Hu, Q. Li, and Z. Hu, "Identification of modal parameters from non-stationary responses of high-rise buildings", *Advances in Structural Engineering*, vol. 24, no. 15, pp. 3519–3533, 2021, doi: 10.1177/13694332211033959.

[15] E. Emami, A. Kheyroddin, and O. Rezaifar, "Eccentricity and slenderness ratio effects of arched steel haunches subjected to cyclic loading; experimental study", *Advances in Structural Engineering*, vol. 25, no. 6, pp. 1339–1356, 2022, doi: 10.1177/13694332211063677.

[16] J. Zhang, Y. Tang, H. Wang, and K. Xu, "ASRO-DIO: Active subspace random optimization based depth inertial odometry", *IEEE Transactions on Robotics*, vol. 39, no. 2, pp. 1496–1508, 2023, doi: 10.1109/TRO.2022.3208503.

[17] M.A. Corsetti and T.M. Love, "Grafted and vanishing random subspaces", *Pattern Analysis and Applications: PAA*, vol. 25, no. 1, pp. 89–124, 2022, doi: 10.1007/s10044-021-01029-0.

[18] E. Plebankiewicz, A. Lesniak, E. Vitkova, and V. Hromadka, "Models for estimating costs of public buildings maintaining-review and assessment", *Archives of Civil Engineering*, vol. 68, no. 1, pp. 335–351, 2022, doi: 10.24425/ace.2022.140171.

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