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Analysis of ASCE Benchmark Structure State Based on Chaotic Time Series Information Entropy

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Abstract: Analysis of Bridge structures state based on the vibration characteristics is gaining more and more attention. Linear theory and technology can not meet the requirements of the structural state analysis because of the nonlinear characteristics of structural materials, geometry and boundary. This study introduces the theory of chaos and the technology of chaotic time series information entropy, analysis the correlation of information entropy and its structural state and monitoring time series information from structural acceleration obtained from ASCE Benchmark model. Extracting of Approximate Entropy, K entropy and constructed information entropy index to reflect the degree of disorder system damage. Expected to use the information entropy theory to solve part of difficulty existing in the analysis of bridge structure state, Provide scientific basis and technical for Bridge structural health monitoring based on Bridge Structural health monitoring information.

Key words: Chaos, time series, K entropy, approximate entropy, structural monitoring, ASCE benchmark

INTRODUCTION

Bridge structure, as a complex mechanical model, with the differences in structure form, materials, environment and other factors, presents nonlinear characteristics in operation. real-time response information on the operation bridge obtained from Structural Health Monitoring System is important information in accordance with a fixed sampling period of dynamic record structure operating activities, it have the nature characteristics of time series. Thereby, through real-time monitoring of bridge response data using time series analysis method to reveal the essential characteristic of bridge itself. Generally, the traditional analysis of bridge structures use linear analysis methods, resulting in the large error in the evaluation of structural during operation, in order to reflect the nature of the structure more accurately, Introduction of the nonlinear analysis method become a development trend. Therefore, the analysis and research of bridge structure status by use of nonlinear time series reveal nonlinear characteristics and evolution of the state of the bridge structure to achieve the assessment of bridge safety status and new research directions of structure control.

In recent years, as important theoretical and technical of nonlinear time series, information entropy has been applied in the medical field of EEG detection, ECG analysis and business management,project management, hydraulic structures reliability analysis,stability analysis of rock and rock mechanics parameters of the probability distribution and other areas (Huang *et al*., 2009; Zhang *et al*., 2007; Sliupaite and Vainoras, 2009; Li and Liu, 2009; Christodoulou *et al*., 2009; Zhou *et al*., 2005; Xu and Ren, 2004; Deng *et al*., 2004). However, there are less research in the field of bridge structure damage,in its infancy, mainly for mechanical field of simple bearing steel tube and steel frame structure model, has obtained certain research achievement.

CHAOTIC TIME SERIES INFORMATION ENTROPY

The study of chaotic from time series began in Packard *et al*. (1980) put forward the theory of reconstructing phase space (Han, 2007; Liu, 2006): Any time evolution of a variable determined the long-term evolution of the system and it contains all the long-term evolution information of all variables in the system.Therefore,the study of the chaotic behavior by

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any single variable time series determined the long-term evolution of the systems.The entropy index of chaotic time series Kolmogorov entropy, Approximate Entropy has played an important role in the aspect of chaotic nature in system characterization.

Kolmogorov entropy: Kolmogorow entropy (In brief K entropy) is the important measure of chaos extent of surface feature system and it represents the extent of loss of system information.
As:

$$C_M(\varepsilon) = \lim_{m\to\infty,\varepsilon\to 0} [\varepsilon^{D_2} \exp(m\tau K)] \quad (1)$$

Take logarithm on both sides:

$$\ln C_m(\varepsilon) = \lim_{m\to\infty,\varepsilon\to 0} (D_2 \ln\varepsilon - m\tau K) \quad (2)$$

For sufficiently large phase space dimension m and sufficiently small scale observation scale ε, when D_2 does not change there is:

$$\ln C_{m+1}(\varepsilon) = \lim_{m\to\infty,\varepsilon\to 0} (D_2 \ln\varepsilon - (m+1)\tau K) \quad (3)$$

Equation 2 minus Eq. 3 we have:

$$K = \lim_{m\to\infty,\varepsilon\to 0} \frac{1}{\tau} \ln \frac{C_M(\varepsilon)}{C_{M+1}(\varepsilon)} \quad (4)$$

Different values of K entropy corresponds with different system states: K = 0, system is performing periodic movement; when K>0, the system is making chaos movement; when K→∞ ,the system is making immediate movement. Hence through calculating K entropy qualitative classification of moving state of system can be made.

Approximate entropy: In 1991, Pineus proposed Approximate Entropy algorithm (Liu *et al*., 2006) (Approximate entropy, abbreviated ApEn), it is mainly from the angle of the measured time series complexity and regularity to measure signal nonlinear properties, better reveal its characteristics and mechanism. The greater complexity of the time series of signals corresponding to greater Approximate Entropy value. This analysis method has characteristics of required less data (100-5000 data points), strong anti-noise ability, applicable to deterministic signals and random signals, have been used in many fields such as physiological electrical signals and mechanical equipment fault diagnosis and obtained achievements. B.Q. Huang applied the Approximate entropy algorithm to the pipe surface defects in non-destructive testing of different signal analysis (Huang *et al*., 2009). The comparison of different defects and non-destructive Approximate entropy shows that Approximate entropy can be used as feature extraction and evaluation criteria of a steel pipe with different defect, the smaller the Approximate entropy, shows that the greater damage of the steel tube, otherwise, the smaller damage of the steel tube. In addition, as the increasing of damage to the mechanical system, the frequency component of the vibration signal will increase, reducing the regularity of the signal, so that the Approximate entropy increases.

Approximate entropy use a non-negative number to represent the complexity of a certain time series. It can measure the probability of generating a new model in the time series, the bigger probability of generating a new model, the more complex the series, It means that the Approximate Entropy more complex the larger the corresponding time series. For a given N points in time series {u (I)}, specific steps (Huang *et al*., 2009) to calculate the Approximate entropy as follows (m represents the dimension of the pre-selected moder is the pre-selected similar tolerance):

- Make the array {u(i)} constitute the m-dimensional vector X(i) in sequence:

$$X(i) = [u(i), u(i+1), \ldots, u(i+m-1)],\ i = 1, 2, \ldots N-m+1 \quad (5)$$

- For i, calculating the distance between the vector X (i) and the remaining vector X (j):

$$d[X(i), X(j)] = \max_{k=0\sim m-1} |u(i+k) - u(j+k)| \quad (6)$$

- Given the threshold r (r>0),for each i, calculating the number of d [X (i), X (j)]≤r and the ratio of the number and the total vector number of N-m +1, denoted by C_i^m (r):

$$C_i^m(r) = \{d[X(i), X(j)] < \text{the number of } r\}/(N\text{-}m\text{+}1) \quad (7)$$

- First, take the logarithm of C_i^m (r), then calculate the average for all i, denoted by Φ^m (r):

$$\Phi^m(r) = \frac{1}{N\text{-}m\text{+}1} \sum_{i=1}^{N-m+1} \ln C_i^m(r) \quad (8)$$

- Then, repeat (1)-(4) process for m+1,get Φ^{m+1} (r)
- Finally, the value of the Approximate entropy is:

$$\text{ApEn}(m,r) = \lim_{N\to\infty}[\Phi^m(r) - \Phi^{m+1}(r)] \tag{9}$$

In general, the limit value exist with probability 1. However, in practical , N would not be ∞,when N is a limited value, according to the above steps we can get the estimate value of ApEn when the length of sequence is N, denoted by:

$$\text{ApEn}(m,r) = \Phi^m(r) - \Phi^{m+1}(r) \tag{10}$$

Obviously, the value of ApEn related to the m and r, with practical experience suggest that m = 2, r = 0.1~ 0.25SD (u) (SD represent the standard deviation of sequence {u (I)}), then the Approximate entropy has a reasonable statistical properties.

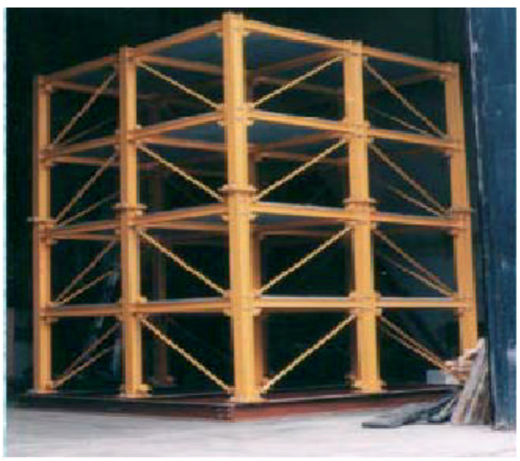


Fig. 1: ASCE Benchmark structure

EXPERIMENTAL ANALYSIS

ASCE benchmark model: ASCE formed a research team of Structural Health Monitoring (SHM) and proposed the establishment of standards for Benchmark structure. ASCE Benchmark (Johnson *et al.*, 2000; 2004) experimental model (as shown in Fig. 1) of a 4-layer, 2 cross×2 cross-scale is a scale model of steel frame, the plane size of the model is 2.5×2.5 m, each layer height is 0.9 meters and the total height is 3.6 m high.

Bench mark test mainly through the dismantling of support or loose connection bolt to simulate the damage of the structure, The experiment measured the motivate and structure dynamic response of the structure in good condition and eight kinds of damage, obtained experimental data under different injury structures. The 9 kinds test conditions of ASCE Benchmark structure as shown in Fig. 2.

According to the test process of Benchmark, the analysis of chaotic time series by test data of next day. In order to corresponding with the finite element model test of Benchmark, the analysis of chaotic time series choose the hammer excitation (incentive) transient dynamic response data. Among them, the X, Y data from sensor 10 as shown in Fig. 3.

State analysis of benchmark model based on k entropy: Entropy K is closely related with the Lyapunov exponent:for one dimensional system K = λ_L^+, that is the K entropy equals to Lyapunov exponent.For structural monitoring, the structure measuring point dynamic

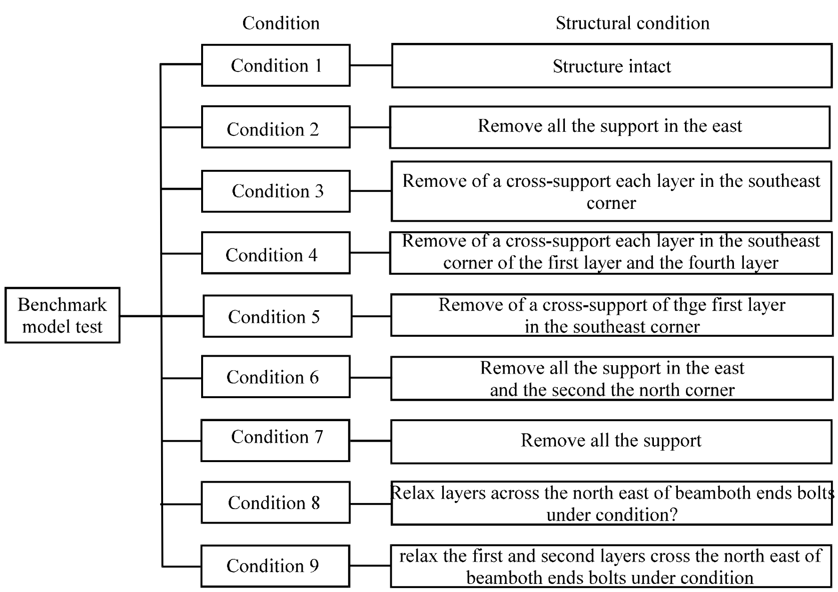


Fig. 2: ASCE Benchmark model test

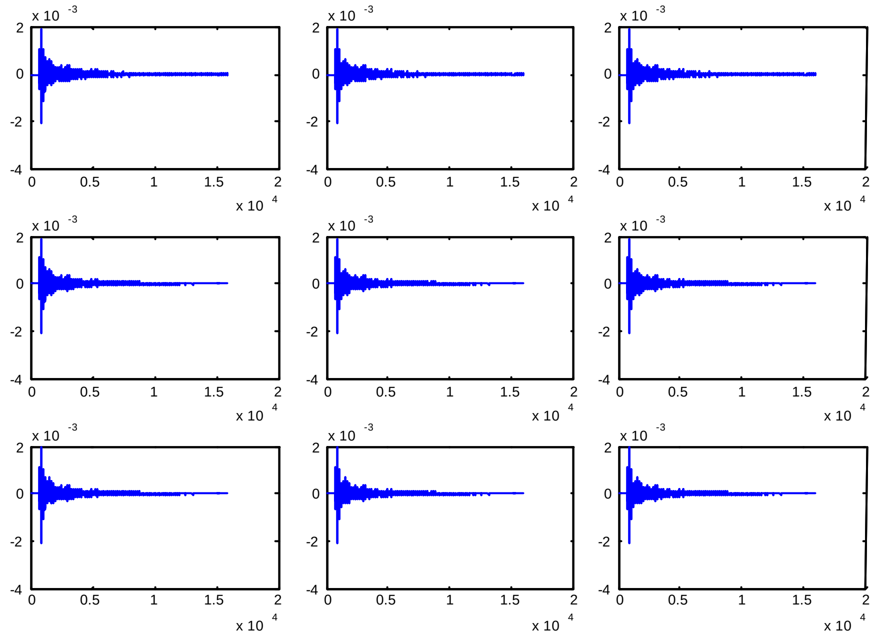


Fig. 3: X, Y direction acceleration excitation in sensor 10 under 9 kinds of working conditions

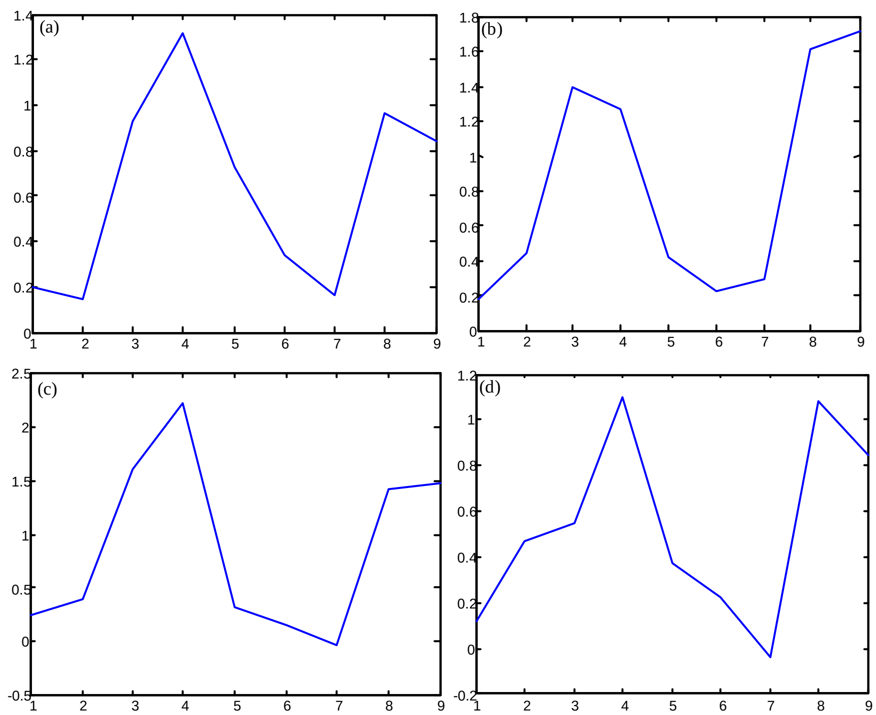
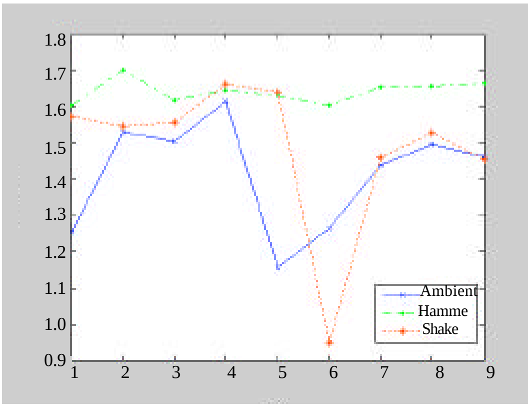


Fig. 4(a-d): Maximum Lyapunov index sensor monitoring information, (a) No.3 sensor, (b) No.9 sensor, (c) No.12 sensor, (d) No.15 sensor

response information from a sensor is acquired one-dimensional chaotic time series, thus, we can use Lyapunov exponent instead of k Entropy. On the basis of acceleration data obtained from 15 effective structural response information, use Wolf methods to extracted largest Lyapunov exponent (K Entropy) of time series from No. 3, 9, 12, 15 sensor, as shown in Fig. 4.



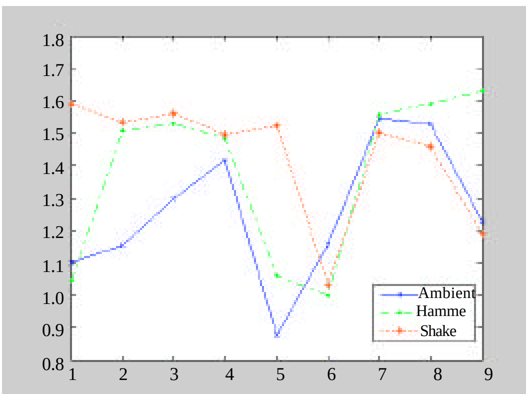


Fig. 5(a-d): Representative sensor monitoring information Approximate Entropy, (a) Approximate entropy of DA03 sensors, (b) Approximate entropy of DA03 sensors, (c) Approximate entropy of DA12 sensors and (d) Approximate entropy of DA15 sensors

Analysis of benchmark model state based on the approximate entropy: Aim at Benchmark model Shaker, Hammer and Ambient three kinds of incentive form, respectively ,approximate Entropy analysis of time series obtained from 16 sensors. The calculation results from DA03, DA09, DA12, DA15 sensor as shown in Fig. 5.

CONCLUSION

Health monitoring system is the important mean of conducting real-time monitoring and assessments of large-scale bridges in service in the domestic and overseas. With the character that the theory of Chaotic time series information entropy represents the complexity of structural system nonlinearity,this text extract the Kolmogorov Entropy and Approximate Entropy with the acceleration gained by the model structure of ASCE Benchmark, aiming at the current situation that there is no effective method to extract information of structure evolution from monitoring data and the lack of maturational theory and technology system about Large structures. Experimental analysis indicates that: (1) The Kolmogorov entropy and Approximate Entropy can represent the evolution of the states of structures, (2) The Kolmogorov entropy and Approximate entropy are related to the type of the incentive to structures, but their performance in general is stable.

Extracting the information of the Kolmogorov entropy and Approximate entropy with the theory of Chaotic time series information entropy is the important mean of carrying out analyzing the state evolution of structures from the dynamical system when they are in service and the safety assessment .The theory and technology of comentropy introduced by this text may lay the experimental foundation of the real-time health and safety assessment of bridges based on the chaotic nonlinear theory.

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REFERENCES

Christodoulou, S., G. Ellinas and P. Aslani, 2009. Entropy-hased scheduling of Resource-constrained construction projects. Automation Construct., 18: 919-928.

Deng, J., X.B. Li and D.S. Gu, 2004. Information entropy inference of Rock mechanics parameters probability distribution. J. Rock Mechanics Eng.,

Han, M., 2007. Prediction Theory and Method of Chaotic Time Series. China Water Power Press, Beijing, pp: 50-92.

Huang, B.Q., H.H. Pan and Z.H. Tang, 2009. The application of approximate entropy in signal analysis of steel pipe Non-destructive testing. Exp. Technol. Manage., 26: 36-38.

Huang, X., Z. Song and W. Zheng, 2009. The evaluation significance of power spectral entropy in the prediction of rat epileptiform. J. Central South Univ. (Med. Sci.), 34: 776-780.

Johnson, E., H. Lam, L. Katafygiotis and J. Beck, 2004. Phase I IASC-ASCE structural health monitoring benchmark problem using simulated data. J. Eng. Mech., 130: 3-15.

Johnson, E.A., H.F. Lam, L.S. Katafygiotis and J.L. Beck, 2000. A benchmark problem for structural health monitoring and damage detection. Proceedings of the 3rd International Workshop on Structural Control Structural Control for Civil and Infrastructure Engineering, July 6-8, 2000, World Scientific, River Edge, Paris, pp: 317-324.

Li, Z.Q. and C.H. Liu, 2009. Entrepreneurial innovation behavior of the system entropy model based on dissipative structure. China Soft Sci., 8: 162-166.

Liu, Z.H., 2006. Fundamentals and Applications of Chaotic Dynamics. Higher Education Press, Beijing, Pages: 71, (In Chinese).

Packard, N., J. Crutchfield, D. Farmer and R. Shaw, 1980. Geometry from a time series. Phys. Rev. Lett., 45: 712-715.

Sliupaite, Z.N. and A. Vainoras, 2009. Eraluation of complexity of ECG parameters using sample entropy and hankel matrix. Electron. Electrical Eng., 4: 107-110.

Xu, C.H. and Q.W. Ren, 2004. Entropy mutation guidelines research based on the stability analysis of surrounding rrock. Rock Soil Mechanics, 25: 437-440.

Zhang, D.Z., X.H. Tan and S.Q. Liu, 2007. Different frequency power spectral entropy and application in ecg analysis. J. Hunan Univ. (JCR Sci. Edn.), 34: 75-79.

Zhou, C.X., X.D. Shen, L.P. Wang and H.L. Wang, 2005. The principle of maximum entropy in analysis of hydraulic construction reliability. J. Fuzhou Univ. (Nat. Sci. Edn.), 33: 115-118.