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# Nonlinear measurements for feature extraction in structural health monitoring

**J.P. Amezquita-Sanchez**[a,*] **and H. Adeli**[b]

a. *ENAP, Faculty of Engineering, Departments of Electromechanical and Biomedical Engineering, Autonomous University of Queretaro, Campus San Juan del Rio, Moctezuma 249, Col. San Cayetano, 76807, San Juan del Rio, Queretaro, Mexico.*
b. *The Ohio State University, Columbus, OH 43210, USA.*

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**Abstract.** In the past twenty-five years, Structural Health Monitoring (SHM) has become an increasingly significant topic of investigation in the civil and structural engineering research community. An SHM schema involves three main steps: (a) measurement and acquisition of signals related to the structural response; (b) signal processing consisting of pre-processing and feature extraction employing nonlinear measurements; and (c) interpretation using machine learning. This article presents a review of recent journal articles on nonlinear measurements used for feature extraction in SHM of building and bridge structures. It also reviews three recently-developed nonlinear indexes with potential applications in SHM.



## 1. Introduction

Civil structures are pillars of the society and economy as they provide protection for the people and communication among different cities, communities, and countries [1-3]. They are exposed to diverse types of potential damages during their service life due to, for example, corrosion [4], loosened bolts, cracks [5,6], among others, produced by natural phenomena and dynamic excitations such as earthquakes, high winds, tornadoes, humidity, wind, and traffic, affecting their performance negatively [7,8]. As such, it is crucial to assess their health conditions and structural integrity continuously because any damage identified in its early stage can be repaired before the occurrence of any catastrophic failure, thus avoiding and/or minimizing potential economic and human losses [9].

In the past twenty-five years, Structural Health Monitoring (SHM) has become an increasingly significant topic of investigation in the civil and structural engineering research community, the industry, and government because SHM provides a process for identifying or evaluating the health condition of a civil structure continuously or in real-time [10-12]. An SHM schema involves three main steps:

(a) Measurement and acquisition of signals related to the structural response such as accelerations;

(b) Signal processing consisting of pre-processing (measured signal conditioning or transformation using time, frequency or time-frequency methods) and feature extraction employing nonlinear measurements;

(c) Interpretation using Machine Learning (ML) and classification algorithms (Figure 1).

*. *Corresponding author. Tel.: +52 1 4272741244*
*E-mail address: jamezquita@uaq.mx (J.P. Amezquita-Sanchez)*

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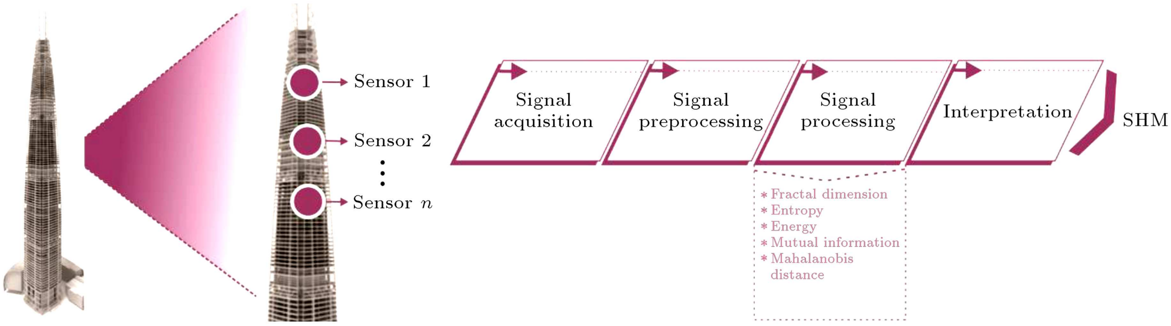


**Figure 1.** Schematic diagram of steps employed in an SHM system.

A review of signal processing techniques for vibration-based health monitoring of civil structures was presented by Amezquita-Sanchez and Adeli [13]. Amezquita-Sanchez and Adeli [14] presented a review of feature extraction and classification techniques for SHM. In the last step of the SHM schema, an ML or classification algorithm such as deep neural network learning [15-18] or Bayesian learning model [19] is employed to determine the health condition or damage state of the structure.

Feature extraction is key to the development and successful application of a classification algorithm [20-23]. Then, a fundamental research question is the choice of the most appropriate measurement for feature extraction. This article presents a review of recent journal articles on nonlinear measurements used for feature extraction in SHM of building and bridge structures.

## 2. Nonlinear measurements used for SHM

Large civil structures are characterized by complicated nonlinear behaviors during dynamic events manifested in their measured responses [24,25]. Hence, it is of paramount importance to have nonlinear measurements or indexes capable of identifying hidden features or patterns in the damaged structure for evaluating its health condition. In this section, nonlinear measurements used for feature extraction in SHM are presented.

### *2.1. Fractal dimension*

Fractal Dimension (FD) is a nonlinear index employed for measuring the similarity encountered in a time signal. It quantifies how many times a pattern is repeated in a time series signal [26,27]. Its value ranges between 1 for low similarity and 2 for high similarity. It has been used for evaluating the health condition of civil structures, because the measured signals can include fractal properties. An and Ou [28] applied the Box Dimension (BD), an FD algorithm, for detecting and locating cracks in a beam. The changes in the FD values produced by the beam curved mode shapes are used for locating the damage zone. The authors reported that the effectiveness of the BD method was dependent on the quantity of noise in the time series signal analyzed. Li et al. [29] combined the Gabor wavelet with the BD method to detect and locate damage in numerical simulation of a 10-story shear-frame. The damage consisted of the yielded zone in the simulated structure. The results showed that the FD method could estimate the changes produced in measured or generated signals. The authors, however, noted that further investigation was needed in order to corroborate these results for real-life civil structures.

Amezquita-Sanchez and Adeli [30] presented a novel Synchrosqueezed Wavelet Transform (SWT)-fractality model for detecting, locating, and quantifying the damage severity in a high-rise building structure. Three different FD algorithms, Katz Fractal Dimension (KFD), Higuchi Fractal Dimension (HFD), and BD, were evaluated for identifying patterns capable of assessing the health condition of the building. The effectiveness of the model was evaluated using data obtained experimentally for the 1:20 scaled model of a 38-storey concrete building structure shown in Figure 2 on a shake table in Hong Kong by Ni et al. [31]. The authors concluded that the SWT integrated with BD provided an effective tool for detecting, locating, and quantifying damage severity in a high-rise building, even in an early light-level damage state. Huang et al. [32] integrated KFD and HFD with a multi-task sparse Bayesian learning [33,34] for detecting and locating damage in the Tianjin Yonghe Bridge, one of the earliest cable-stayed bridges in the mainland of China (see Figure 3). The authors concluded that the FD method could be potentially an effective SHM tool, but additional investigations are required to verify that.

### *2.2. Entropy*

Entropy is a nonlinear index capable of measuring the randomness found in a time series signal [35]. The entropy index has provided good results in different fields such as medicine and physiology [36] and mechanical engineering [37]. Li et al. [38] presented numerical results combining artificial neural networks, Dempster-Shafer theory, and Shannon entropy for detecting dam-

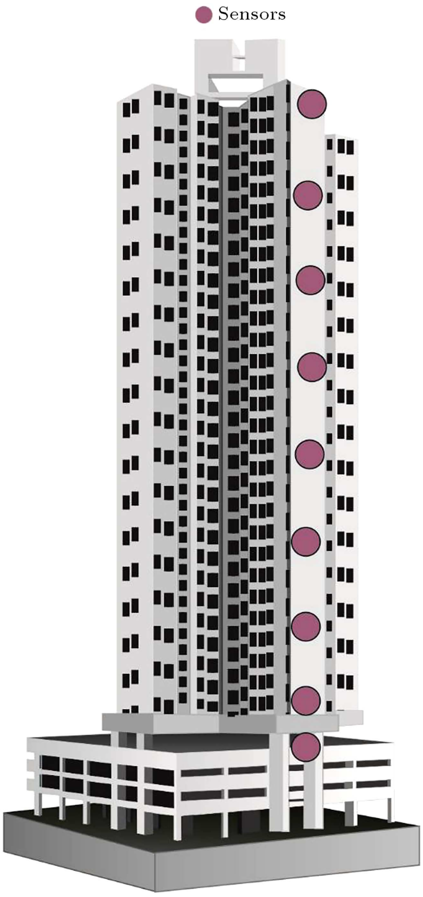


**Figure 2.** High-rise building model (adapted from Ni et al. [31]).

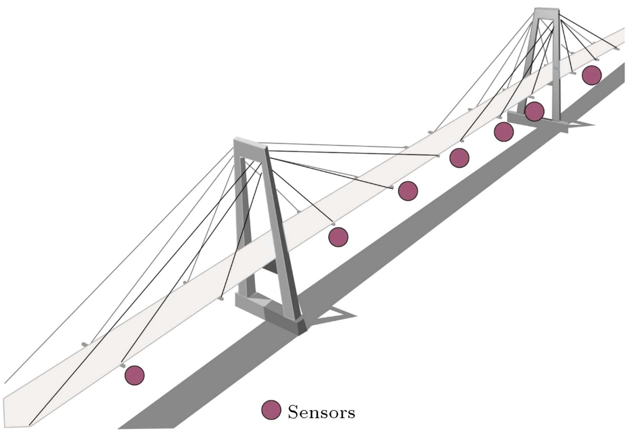


**Figure 3.** The layout of the accelerators for Yonghe Bridge (adapted from Huang et al. [32]).

age in the Binzhou Yellow River highway bridge, where damage in the elements was simulated by a reduction in element stiffnesses. The authors pointed to Shannon entropy as a useful tool for measuring the uncertainty level of the damage decision. González et al. [39] used the Cross-Sample Entropy (CSE) for detecting damage in a beam subjected to dynamic loads. They noted that the CSE was susceptible to noise contained

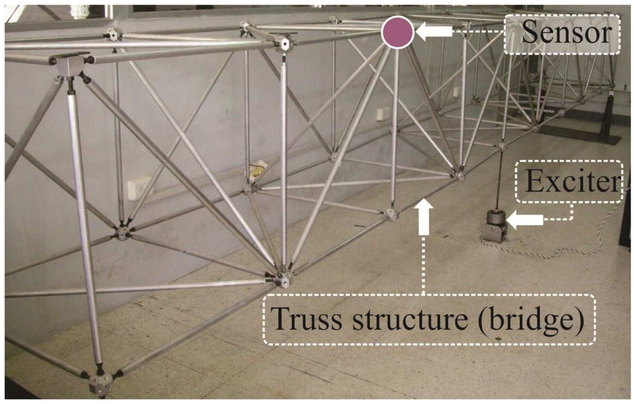


**Figure 4.** 3D 9-bay truss-type bridge with corrosion damage (adapted from Moreno-Gomez et al. [41]).

in the time series signal, which could produce errors to correctly diagnose the health condition of a civil structure. Lin and Liang [40] compared the Multi-Scale Entropy (MSE) with Multi-Scale Cross-sample Entropy (MSCE) for detecting and locating damage in a seven-story frame subjected to ambient vibrations. The authors reported that combining both methods could lead to more accurate results.

Incipient or light damage represents a challenge to its identification in SHM. Moreno-Gomez et al. [41] proposed the fusion of the Empirical Mode Decomposition (EMD) [42] and Shannon entropy for detecting damage due to corrosion in a 3D 9-bay and 169-member truss-type bridge subjected to dynamic excitations, as shown in Figure 4. The authors noted that the integration of both methods allowed identifying light damage produced by external corrosion starting from 1 mm reduction in the bar element diameter. Wang et al. [43] presented an entropy-based active sensing method for monitoring early looseness of multi-bolt connections. Other applications of entropy in SHM were presented by Ren and Sun [44], Amiri et al. [45], and Meruane and Ortiz-Bernardin [46].

### 2.3. Energy index

The energy index is defined as the area under the squared magnitude of a time series signal and is defined mathematically as follows [47]:

$$E = \sum_{i=1}^{N} |\mathbf{x}_i|^2 , \tag{1}$$

where $\mathbf{x}$ is the amplitude of a time series signal with $N$ points.

Because of its easy implementation, the energy index has been employed in different fields such as biomedical, electrical engineering, among others [48].

In the past decade, the energy index was applied to SHM. Razi et al. [49] employed the Empirical Mode Decomposition (EMD) for detecting and quantifying cracks in a steel beam. The energy of the first frequency band estimated by EMD method is used to assess the health condition of the beam. Garcia-Perez et al. [50] fused the wavelet transform [51,52] and EMD methods for detecting and locating loosened bolts and internal and external corrosion, as well as their combinations in a 3D five-bay 70-member cantilever truss structure. The authors noted that the combination of the energy rate from both methods could be used as an indicator for locating the damage zone. Facchini et al. [53] employed the wavelet transform and energy for detecting damage in a beam subjected to dynamic excitations produced by a shaker.

Recently, the efficacy of the wavelet packet transform [54] with energy index was evaluated by Pan et al. [55]. They used the accelerations of the Wangzong tunnel in the Wuhan Metro Line 3 in China subjected to dynamic excitations for evaluating its health condition. The authors reported an efficiency rate of 98%, but their approach required that a sensor or sensors be placed next to the damage zone, which is usually not realistic and practical. Other applications of energy in SHM were presented by An and Ou [56] and Suarez et al. [57].

### *2.4. Mutual information*

Mutual Information (MI) is known as a nonlinear index capable of capturing and measuring the dependence between two random variables or signals that are being monitored simultaneously. In other words, it measures how much information is related to one variable about another [58]. In this sense, MI allows analyzing linear and nonlinear signals in many fields such as systems identification, condition monitoring of rotating machinery, atmospheric changes, among others [59,60] because the monitored signals exhibit nonstationary behaviors. Because of this advantage, MI has been employed for health monitoring of civil structures since they present nonlinear behaviors. Trendafilova et al. [61] compared the MI and Cross Correlation (CC) methods for the damage detection of a simple 2 degree-of-freedom mechanical system, where nonlinear stiffness was suggested as damage. The authors concluded that the MI method could detect linear and nonlinear signal dependence, but the CC method failed to detect the nonlinear behaviors encountered in the signals. Sudu-Ambegedara et al. [62] used the MI method for detecting loosened bolts in the Waddington bridge located in New York State Route 345 over Big Sucker Brook in the town of Waddington, New York, subjected to dynamic vibrations produced by a truck (Figure 5). The results showed that the proposed method required comparison with a baseline case, a healthy structure; however, in certain cases, it is not possible to have a baseline case to determinate if the structure is healthy, especially in old structures.

Recently, Perez-Ramirez et al. [25] presented a recurrent neural network model [63] with Bayesian training [64,65] and MI for response prediction of large building structures. Babajanian-Bisheh et al. [66] introduced the MI method for selecting the most discriminate features estimated in time, frequency, and time-frequency domains for evaluating the health condition of the Tianjin Yonghe Bridge, a cable-stayed bridge, located in China subjected to ambient vibrations. The results demonstrated that the MI method was a good tool for selecting adequate features in order to evaluate the health condition of the bridge as it reduced the false alarm.

### *2.5. Mahalanobis distance*

Mahalanobis Distance (MD) method is a statistical index capable of measuring how similar a set of features or signals are to a known set of conditions by calculating the covariance among them [67]. MD method can measure the similarity/dissimilarity between two signals. It has been applied for analyzing data obtained in rotating machines [68], financial problems [69], classification [70], fault detection [71], and saliency prediction [72], among other applications.

A few applications of MD method have been reported for damage detection in recent years. Mosavi et al. [73] combined vector autoregressive models with MD method for identifying and locating damage in an idealized steel bridge girder subjected to ambient vibrations. The MD index of the coefficients of the vector autoregressive is employed for assessing the health condition of the simulated bridge. Zhou et

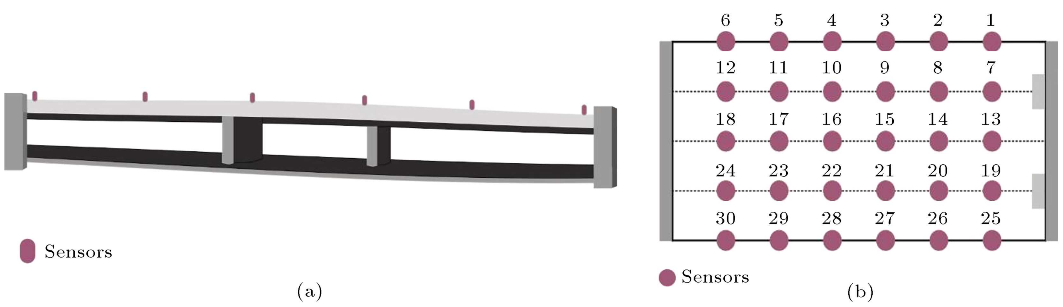


**Figure 5.** (a) the Waddington Bridge and (b) sensors location (adapted from Sudu-Ambegedara et al. [62]).

al. [74] examined the MD method for detecting crack in a beam subjected to dynamic excitation produced by a shaker. The authors reported the method could detect and quantify the severity of damage, but cannot estimate the damage location. George et al. [75] tested the MD index for detecting damage in a numerical simulation of a ten-story shear frame subjected to dynamic vibrations.

## 3. New nonlinear measurements

In this section, recently-developed nonlinear measurements with potential application in SHM are reviewed.

### *3.1. Sevcik fractal dimension*

Proposed by Sevcik [76], Sevcik's fractal dimension is the latest in the string of FD approaches for measuring the complexity and randomness of time series signals. It provides good robustness to noise in noisy signals and is easy to implement. It has provided good results in the analysis of communication signals [77] and vibration signals [78]. It has not been used in any structural engineering applications.

### *3.2. Visibility graph*

Visibility Graph (VG) algorithm was introduced by Lacasa et al. [79] for mapping a time series signal to a graph to study its complexity and fractality. VG has been used as a diagnostic EEG marker for the Alzheimer's disease [80], for classification of epileptiform in EEG signals obtained from epileptic patients [81], and most recently for analysis of speech evoked auditory brainstem response in persistent developmental stuttering [82]; however, its robustness and performance for estimating the complexity of a time series signal under noisy signals can be compromised. Ahmadlou et al. [83] introduced the Power of Scale-freeness of VG (PSVG) to improve the accuracy and robustness of VG to noise for measuring the fractality of a time series signal. Ahmadlou and Adeli [84] presented Visibility Graph Similarity (VGS) as a new measure of generalized synchronization in coupled dynamic systems. Applications of the improved PSVG and VGS algorithms for health monitoring of large structures are worth exploring.

### *3.3. Dispersion entropy*

Entropy methods such as sample entropy and permutation entropy are susceptible to error in noisy signals, and they consider only the order of the magnitude values. As a result, some information regarding the magnitudes may be inadvertently discarded. For lessening these problems, Rostaghi and Azami [85] introduced a new entropy method, named dispersion entropy, a nonlinear index capable of measuring the complexity and uncertainties encountered in a time signal, which considers simultaneously the changes in frequency and amplitude of the time series signal. It has been used in mechanical [86] and biomedical engineering [87] applications. Its application in SHM is worth exploring.

## 4. Conclusions

This paper presented a review of the main nonlinear measurements used in SHM. It also reviewed three recently-developed nonlinear indexes as potential applications in SHM. Additional research is required to select measurements or features for SHM schema to be realized for large real-life structures such as bridge and high-rise building structures.

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## Biographies

**J.P. Amezquita-Sanchez** graduated from University of Guanajuato in 2007 with a BSc Degree in Electronic Engineering. He received his MSc degree in Electrical Engineering from University of Guanajuato and the PhD degree in Mechatronics from the Autonomous University of Queretaro, Queretaro, Mexico in 2009 and 2012, respectively. He was a Postdoctoral Visiting Scholar in The Ohio State University during 2013-2014. He is currently a full-time Professor at the Faculty of Engineering, Autonomous University of Queretaro, Campus San Juan del Rio, Queretaro, Mexico. He is a member of the Mexican National Research System (SNI), level 1. He has published in the areas of structural health monitoring, signal processing, and mechatronics.

**Hojjat Adeli** received his PhD from Stanford University in 1976 at the age of 26. He is currently an Academy Professor at The Ohio State University where he held the Abba G. Lichtenstein Professorship for ten years. He is the Editor-in-Chief of the international journals Computer-Aided Civil and Infrastructure Engineering, which he founded in 1986, and Integrated Computer-Aided Engineering, which he founded in 1993. He has authored over 600 research and scientific publications in various fields of computer science, engineering, applied mathematics, and medicine, including 16 ground-breaking high-technology books. He is the recipient of sixty three awards and honors including four Honorary Doctorates, and Honorary Professorship at several Asian and European Universities. In 2005, he was elected a Distinguished Member, ASCE: "for wide-ranging, exceptional, and pioneering contributions to computing in civil engineering and extraordinary leadership in advancing the use of computing and information technologies in many engineering disciplines throughout the world." He is a member of Academia Europaea, a corresponding member of the Spanish Royal Academy of Engineering, a foreign member of Lithuanian Academy of Sciences and Polish Academy of Science, and a Fellow of AAAS, IEEE, AIMBE, and American Neurological Association.