Development of a Bio-Inspired Structural Health Monitoring System Based on Multi-Scale Sample Entropy

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Development of a Bio-inspired Structural Health Monitoring System Based on Multi-scale Sample Entropy

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ABSTRACT

A bio-inspired structural health monitoring (SHM) system based on multi-scale Sample Entropy (SampEn) is proposed in this paper. Recently, studies on entropy have shown that the healthy state of human can be evaluated by analyzing the measured electrocardiogram. As similar circumstance is also faced in the field of structural health monitoring, where the vibration signal of the structure can be measured by deployed sensors, a multi-disciplinary research is inspired and conducted. Numerical simulation has verified that the damage location and condition can be detected by the proposed SHM algorithm by processing the ambient vibration signal.

KEYWORDS：*Structural health monitoring, Multi-scale entropy, Sample entropy*

INTRODUCTION

The concept of structural health monitoring (SHM) is generally defined as the numerical process to evaluate the physical parameters or visual inspection of fracture or crack on the structure. Based on the evaluation process, the detection method can be roughly classified as destructive evaluation (DE) and Non- Destructive Evaluation (NDE). Over the last decade, operational modal analysis, a new concept belonging to NDE, has been proposed. Comparing to traditional method, the rapid and low-cost advantages the operational modal analysis has made it a new direction for implementing SHM on practical structures [1,2]. Therefore, the multi-scale entropy method based on operational modal analysis is introduced in this study.

Entropy was originally used to evaluate the uncertainty of specific events. The first application of entropy was found in the field of thermodynamics. Shannon introduced the concept of entropy into information theory, and the Shannon entropy was proposed [3]. As noise is contained in the experimental data, a series of analysis method named approximate entropy (ApEn) was proposed by Pincus to solve the problem that no entropy can be extracted from some experimental data [4]. Based on ApEn, Richman and Moormanp developed sample entropy (SampEn) [5]. Comparing to ApEn, the SampEn will not be affected by the length of the time series, and became the main stream for entropy analysis. The multi-scale entropy (MSE) was first proposed by Costa in 2002 [6,7]. To effective extract the information from the signal, the coarse-graining process was used for data pre-processing to improve the accuracy of . The MSE was used to analyze mechanical vibration signal, which mainly focuses on the bearing under different operation conditions by Shuen-De Wuet al. in 2013 [8]. The complexity of the system can be reflected by the result of MSE as a basis of real-time monitoring. An damage index was also proposed to identify the malfunction condition of rotors.

The cross- approximate entropy (Cross-AnEn) was first proposed by Pincus and Singer in 1996 [9]. Based on Cross-AnEn, the cross-sample entropy (Cross-SampEn) was developed by Richman and Moorma in 2000, where the similarity degree between two signals of the same system is defined [10]. Performance of Cross-SampEn has been pointed out to be obviously better than Cross-AnEn for evaluation of the synchronization degree between heart beat rate and chest volume. Relationship of exchange rate fluctuation to US dollar for south-east countries during the 1998 Asia financial crisis was evaluated by Cross-SampEn by Li-Zhi Liu in 2010 [10]. As shown in the report, the Cross-SampEnvalue was quite low for several countries before the financial crisis, which indicates that similar policy and economic activity were conducted. As countries changed their economic policies to face the crisis, and exchange rates started to diverge, the Cross-SampEn became comparatively high after. The vocal disorder was analyzed by Cross-SampEn in 2013 by Chiara Fabris [11] Two sound signals including the signals from microphone (MIC) and electroglottograph (EGG). By calculating the Cross-SampEn from the EGG and MIC signals for the synchronization degree, the possible reason to cause the pathological subjects can be identified as the values are relatively small for normal subjects.

As the dynamic response of structure is analyzed under the scale factor of 1 in traditional method, where different damage condition may not be reflected significantly, the MSE method will be introduced in this study for better identification result. The Cross-SampEn method to analyze the relationship of signals of different floors under the same damage condition will also be applied for the possible damage location.

THEORY

Multi-scale Entropy (MSE) Method

Since result from Sample Entropy (S_E) is not affected by the length of the time series and better consistency can be expected under different parameter settings, S_E is commonly preferred among various methods of calculating the entropy of the system. As the multi-scale entropy (MSE) method basically follows the same process of (S_E), theory of S_E is first introduced. Suppose a time series $\{X_i\} = \{x_1,...,x_i,...,x_N\}$ with length N, a vector $u_m(i) = \{x_i, x_{i+1},...,x_{i+m-1}\}, 1 \le i \le N-m+1$ of length m can be defined as the sample. The sample space T, which is the *N*-*m*+1combination of all samples with length m, is further defined as *T* where $\{x_j, x_{j+1},...,x_{j+m-1}\}$ represents the jth sample

$$T = \begin{pmatrix} x_1 & x_2 & \cdots & x_m \\ x_2 & x_3 & \cdots & x_{m+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N-m+1} & x_{N-m+2} & \cdots & x_N \end{pmatrix} \tag{1}$$

Let $n_i^m(r)$ be the number of similarity between sample $u_m(j)$ and $u_m(i)$ where the similarity is defined as $d[u_m(i), u_m(j)] \le r$; r is a predetermined threshold, and d is the maximum distance between the two samples, which can be calculated by

$$d_{ij} = \max\{| x(i-k) - x(j+k) |: 0 \le k \le m-1\} \tag{2}$$

The probability of sample similarity can be defined as $U_i^m(r) = n_i^m(r)/(N-m+1)$. Through calculating the average probability of samples with length m, $U^m(r) = 1/(N-m+1)\sum_{i=1}^{(N-m+1)} U_i^m(r)$, the average similarity probability can be obtained. Following the same procedure, the average similarity probability $U^{m+1}(r)$ of length $m+1$ can be estimated, and the sample entropy of parameters *m, r*, and *N* can finally be calculated as

$$S_E(m,r,N) = -\ln \frac{U^{m+1}(r)}{U^m(r)} \tag{3}$$

It is worth noting that when calculating the sample similarity, the sample is not compared with itself. The threshold r is presented by a specific percentage of the standard deviation (SD) of the original time series to avoid the influence from the amplitude. In order to evaluate the time series under different time scales, the MSE converts the original signal through a coarse graining procedure and the corresponding S_E values can be calculated individually to reflect the possible anomaly.

For a discrete time series $\{x_1,...x_i,...,x_N\}$ with length N, the original signal is first divided into multiple non-overlapped windows with τ points as shown in Figure 1. A new time series $\{y^{(\tau)}\}$ can then be generated through the coarse graining procedure by taking the average value of each window as

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, \quad 1 \le j \le N/\tau \tag{4}$$

where τ is defined as the scale factor.

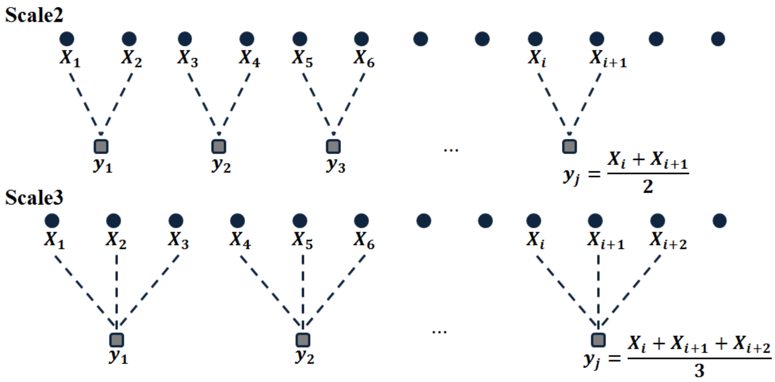


Figure 1: The coarse graining process

The sample entropy S_E is conducted for every time scale $\{y^{(\tau)}\}$, and the function $f(\tau) = S_E$, which is defined as the multi-scale entropy (MSE) analysis, can be illustrated. Different from the original sample entropy analysis, where only a single value can be obtained, the complexity of the dynamic system can be reflected by the distribution of MSE value in different time scale. Therefore, two characteristics are investigated for MSE analysis:

(i) For a signal where the entropy value is larger than another signal among most of the time scale, the system can be classified with more complexity.

(ii)If the MSE curve decreases monotonically with the increase of time scale, only information is contained for the original time scale 1.

Cross-sample Entropy (Cross-SampEn) Method

Cross-sample Entropy (Cross-SampEn) method is another entropy analysis derived from sample entropy. The main purpose of Cross-SampEn is to evaluate the dis-synchronization/dissimilarity degree of two signals measured from the same system. In order to avoid the influence of amplitude, the original time series are normalized by subtracting with the mean value and dividing by the

Standard deviation (SD) before the Cross-SampEn process. The mean value and SD can be tuned to 0 and 1, respectively. The estimation of Cross-SampEn can be summarized as follow: $\{X\}=\{x_1,...,x_i,...,x_N\}$ and $\{Y\}=\{y_1,...,y_i,...,y_N\}$ represent two individual time series with length of N. The signals are detached into pattern templates of length m $u_m(i)=\{x_i,x_{i+1},...,x_{i+m-1}\},1\le i\le N-m+1$ and $v_m(j)=\{x_j,x_{j+1},...,x_{j+m-1}\},1\le j\le N-m+1$, and the template space can be expressed as $T_x=[u(i)u(i+1)\cdots\cdots u(i+m-1]^T$ and $T_y=[v(j)v(j+1)\cdots\cdots v(j+m-1]^T$, respectively. The similarity number between $u_m(i)$ and $v_m(j)$, defined as $n^m(r)$, is calculated by Equation (2) under the criterion of $d[u_m(i)v_m(j)]\le r$. Through the similarity probability, defined as $U_i^m(r)(v\,\|\,u)=n^m(r)/(N-m)$, the average similarity probability of length m can be evaluated by $U^m(r)(v\,\|\,u)=1/(N-m)\sum_{i=1}^{N-m}U_i^m(r)(v\,\|\,u)$ .The Cross-SampEn can finally be derived by the average similarity probability $U^{m+1}(r)(v\,\|\,u)$ of length m+1 as

$$C-S_E(m,r,N)=-\ln\left\{\frac{U^{m+1}(r)(v\,\|\,u)}{U^m(r)(v\,\|\,u)}\right\} \tag{5}$$

In this study, the ambient vibration signals of different stories (channels) are assumed to reflect the same characteristic of the structure. Therefore, the variation of dissimilarity between two signals can be estimated by the combination of MSE and Cross-SampEn as shown in Figure 2. The flowchart of the proposed SHM system can be illustrated by Figure 3. The damage condition is first analyzed by utilizing the MSE method. Through the dissimilarity among channels, the Cross-SampEn is then applied on signals from different stories under the same damage condition or signals of same story but different damage location to detect the damage location

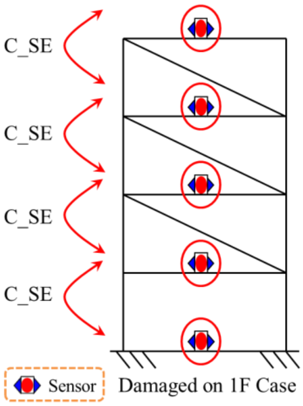


Figure 2:Concept of Cross-sample Entropy Method

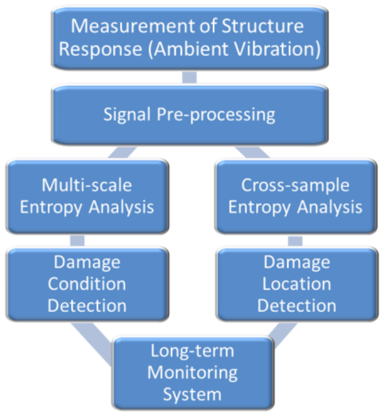


Figure 3: The proposed structural health monitoring process

NUMERICAL SIMULATION

In order to verify the performance of the proposed bio-inspired structural health monitoring system, a series of numerical analysis is conducted on a benchmark steel structure. The ambient response of the structure is simulated by exciting the numerical model established by finite element method with small white noise signal. Different damage conditions and locations are numerically simulated for the verification process.

The 4-story benchmark steel structure used in this study is shown in Figure 3. The height of each story is set as 160 cm and the length and width of the floor are both set as 200 cm. To make the specimen more practical, four 120-kg mass blocks are mounted on each floor. Velocity response of the mass center of each floor is simulated to reflect the characteristic of the structure.

As the damage condition and location are complicated and hard to define in practical buildings, damage modes are roughly classified in this study. Instead, the main objective of the system is a rapid and reliable result, and the success of the system can be a strong basis for the improvement in the future. As shown in Figure 3, the original structure is equipped with two bracings in the weak axis direction, and the damage of the specimen is simulated by removing the bracing of a specific location. The braced and unbraced conditions are clearly illustrated in Figure 4, and the numeral model of the whole specimen is expressed in Figure 5.

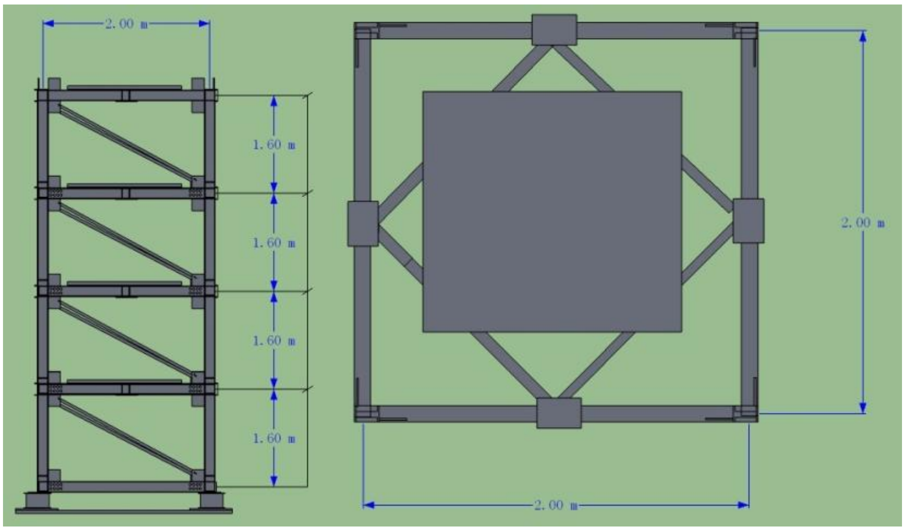
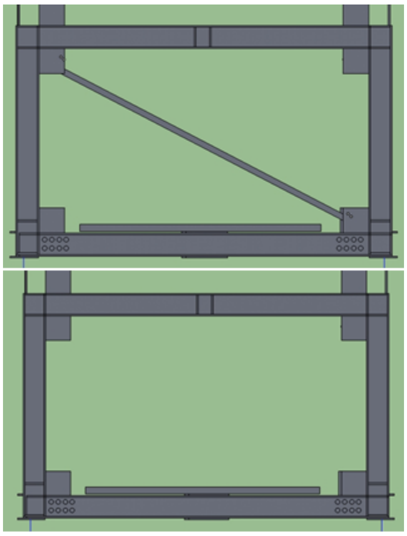


Figure 3: Side view and Top view of the benchmark steel structure



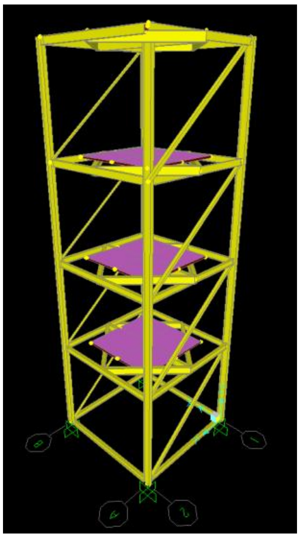


Figure 4: Expression of bracing and unbracing

Figure 5: Numeral model of the specimen

The ambient response of 4-story benchmark structure is limited to linear elastic range when conducting the numerical simulation using software SAP2000. Totally 11 damage cases of five damage categories are simulated as the database for verification. The damage group is classified as (1) undamaged, where no damage is observed on the structure, (2) slight damage, where damage is investigated on a single floor the structure, (3) moderate damage, where damage occurs on any two floors of the structure, (4) severe damage, where damage is found on any three floors of the structure, and (5) ultimate, where damage is observed on any four floors of the structure. Detail of the damage group and floors is listed in Table 1.

Table 1: List of damage group and floors

Case Number	Damage Group	Damage Floors
1	Undamaged	None
2	Slight	1F
3		2F
4		3F
5		4F
6	Moderate	1 & 2F
7		2 & 3F
8		3 & 4F
9	Severe	1 & 2 & 3F
10		2 & 3 & 4F
11	Ultimate	1 & 2 & 3 & 4F

VERIFICATION

As the MSE method is commonly applied in the field of physiological, medical, and mechanical engineering, parameters used in previous researches are set as a basis for analyzing the dynamic response of structure. Based on the performance of the proposed SHM system, the parameters are then tuned and optimized. As shown in the previous studies, the template length is set to 2, and the threshold r is set as 0.15*SD. The scale factor arranged from 1-20 and 1-30 for the MSE and C-S_E, respectively.

MSE analysis is first conduced for five damage cases where the damage location is located in the lower floors to detect the possible damage condition, and the trend analyzed from signal of the third floor is shown in Figure 6. The result has demonstrated that the damage condition can be reflected correctly by calculating the SampEn. The unclear damage condition indicated with scale 1 can be elucidated by increasing the scale gradually.

Following the MSE analysis, signals are processed by Cross-SampEn to identify the damage location. As shown in Figure 7, the undamaged case is first evaluated by signals of two adjacent floors as the reference of healthy condition. Results of different slight damage cases are shown in Figures 8-11, respectively. For the case of damage on the first floor, the Cross-SampEn curves of Channel 1F-2F, Channel 2F-3F, and Channel 3F-4F coincide, which means similar conditions are observed between these floors. However, due to the damage occurred on the first floor, larger Cross-SampEn value can be observed for curve ground-1F. The possible damage can also be indicated by the trend of the curve in Figure 8. For the case of damage on the second floor, the curve of Groud-1F in Figure 9 follows the same trend as that of the undamaged case, and the first floor can be identified as undamaged. Comparison between Figures 7 and 9 indicates that the curves of Channel 1F-2Fare not compatible for high scale factors, and the damage location can be assessed on the second floor. Similarly, the damage location on third floor can be detected by the curve of Channel 2F-3F in Figure 10. As indicated, larger Cross-SampEn value is observed in the range of high scale factor, and the damage location can be determined. The damage location on the fourth floor can finally be pointed by comparison between Figures 7 and 11 where significant change is found on the curve of Channel 3F-4F. The feasibility of the proposed SHM system based on MSE and Cross-SampEn has been successfully demonstrated.

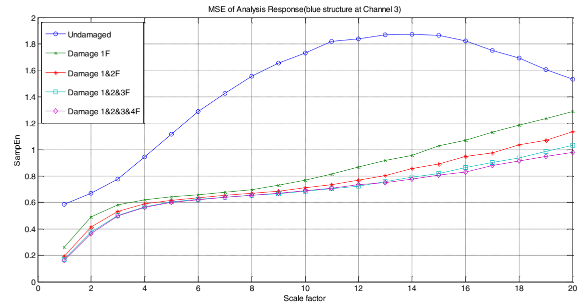


Figure 6 SampEn trend analyzed from signal of the third floor

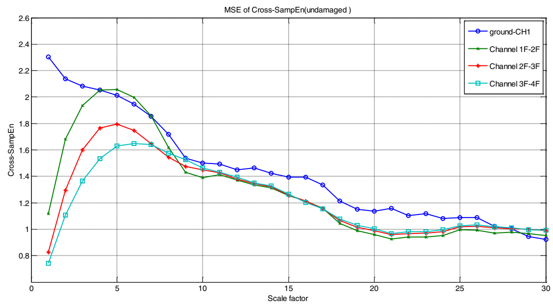


Figure 7 Cross-SampEn trend analyzed from signal of different floors of undamaged case

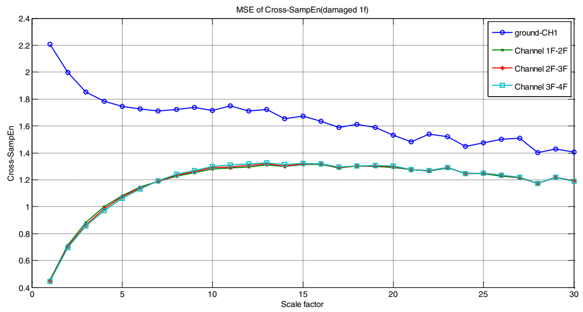


Figure 8 Cross-SampEn trend analyzed from signal of different floors of damaged 1F case

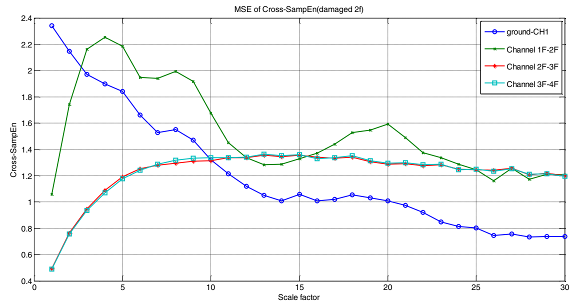


Figure 9 Cross-SampEn trend analyzed from signal of different floors of damaged 2F case

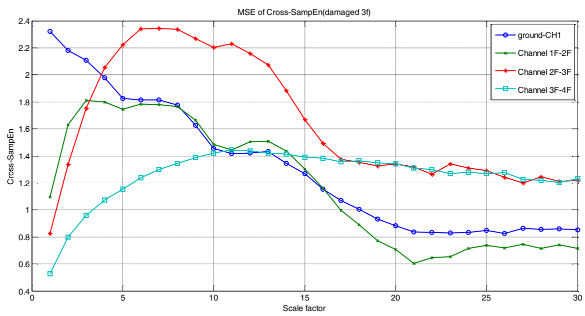


Figure 10 Cross-SampEn trend analyzed from signal of different floors of damaged 3F case

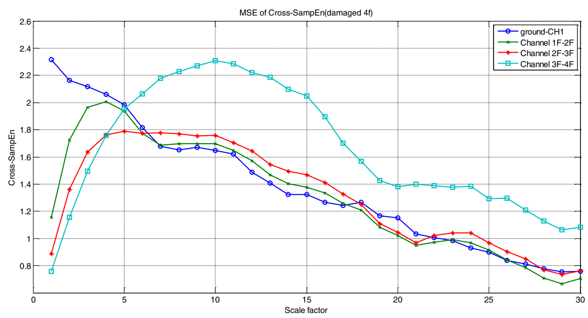


Figure 11 Cross-SampEn trend analyzed from signal of different floors of damaged 4F case

CONCLUSION

As MSE has been widely applied in the field of physiological, medical, and mechanical engineering, a bio-inspired SHM algorithm based on MSE is proposed in this study. A four-story steel structure under different damage conditions and locations is simulated numerically by finite element model, and the structural response is analyzed by MSE and Cross-SampEn method for damage detection. As shown in the result, the damage condition can be significantly identified under large scale factor through the MSE analysis. In the mean time, the damage location can be determined through comparison of Cross-SampEn between undamaged and damaged cases. Numerical simulation has demonstrated that the combination of the two entropy-based methods can be used to develop a bio-inspired SHM system. As only the ambient vibration signal, which is treated as the heart beat of the structure, is required, a rapid and reliable SHM system can be expected.

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