結合感測、系統識別及健康診斷技術

探討橋梁結構破壞預警模式及機制（I）

Integration of Sensing System, System Identification and Health Monitoring Technologies for Damage Prognosis of Bridges (I)

主管單位：交通部中央氣象局　計畫編號：MOTC-CWB-100-E-06

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摘要

近年來台灣有許多橋梁在颱風侵襲期間因為暴漲的溪水或土石流沖蝕，導致橋面板的陷落及橋體的損壞，造成人命傷亡與經濟損失。當務之急除了針對現有橋梁進行整體安全性評估之外，將來更需要發展準確與可靠的橋梁監測系統，對橋梁的安全性進行即時的監測，並在橋梁損害發生與倒塌之前提供預警訊息，以減少人命與經濟財產的損失。本研究利用無線傳輸技術，開發以振動量測為基礎的橋樑監測平台，並採用遞迴隨機子空間識別法(Recursive Stochastic Subspace Identification, RSSI)對收集之量測訊號進行分析，以及開發橋梁損壞指標，以達到橋梁監測與預警之目的。該監測平台已成功應用至實驗室縮尺橋梁模型試驗，以及現地宜蘭牛鬥橋微振動的長期監測。

關鍵詞：無線傳感、系統識別、結構健康診斷、損壞評估

Abstract

Recently during the typhoon season there were several bridges were collapse due to heavy storm in Taiwan. As well as the overall investigation of bridge capacity and safety, it is necessary to develop a health monitoring system to monitor bridge safety and offer early warning while bridge damage and before it collapses. The objective of this study is to develop a reliable bridge structure health monitoring system directly from its vibration measurements under operation conditions by wireless sensing network to monitor bridge safety. Through the output-only measurements, on-line system identification algorithm and damage detection methodologies are developed. Verification of monitoring system and these methodologies is conducted through the large-scale lab test of bridge scouring and long-term field test of Nu-Do Bridge at Yilan.

Keywords：wireless sensing network, system identification, structural health monitoring, damage detection

1. INTRODUCTION

Recently during the typhoon season several bridges collapsed due to heavy storm in Taiwan. Bridge was designed with very strong pier in Taiwan and it is impossible to have damages caused by the direct impact of flood (except the severe debris flow). The major reason for bridge collapse during typhoon and flood is the bridge scouring and this scouring may empty the foundation soil and cause the reduction of bridge bearing capacity. There are over 150 bridges in Taiwan have this kind of potential damage. Therefore it is necessary to develop a structural health monitoring system for bridge to monitor bridge safety and offer warning message to avoid loss of life.

The objective of this study is to develop a reliable structural health monitoring system for bridge based on its vibration measurements under operation conditions. Through the output-only measurements, on-line system identification algorithm and damage detection methodologies are developed to monitor bridge safety. Verification of these methodologies through the large-scale lab test of bridge scouring and long-term field test of Nu-Do Bridge at Yilan is conducted. Based on the data collected from the experimental scouring test of bridge structure, the features of bridge vibration for damage early warning are investigated.

2. EXPERIMENTAL SETUP OF BRIDGE SCOURING TEST

A four span bridge model with simply supported girder on each pier was constructed to across a flume of width 4.0 meter in the hydraulic lab. The span length is about 1.0 m. The sketch and the dimension of this bridge are shown in Figure 1. The bridge piers are embedded in sand with depth of 30 cm. 12 velocity sensors are deployed along the bridge deck to collect the vibration signal of the bridge during scouring process in transverse direction (along stream line). Photos of the bridge during and after test are shown in Figure 2. Velocity response data of the bridge during scouring process are collected. The VSE-15D sensor is used and it is a servo velocity meter produced by Tokyo Sokushin Co., Ltd. This sensor is very sensitive to detect the low level vibration motion and the linear range (0.2Hz~70Hz) is suite for SHM applications. Data acquisition system collected the velocity response of the bridge from all twelve sensors with sampling rate of 200 Hz. Camera was also installed in each bridge pier to observe the scouring phenomenon. Figure 3 shows data from sensor node #2 and node #9, and the scouring depth from the observation. The total run time on this bridge scouring test is 200 min (12,000 sec). All the test setup will be good for on-line monitoring of the bridge structure.

3. ON-LINE SYSTEM IDENTIFICATION METHODOLOGY

The recursive stochastic subspace identification (RSSI) algorithm is used for conducting operational model analysis through output-only measurements. A new RSSI algorithm has been proposed to avoid the use of singular value decomposition [1]. This algorithm consist of two steps: (1) update the LQ decomposition; (2) update the column space of extended observability matrix. The first step implies that the LQ decomposition needs to be updated as long as there is a new set of data provided. The second step on updating algorithm was proposed how to update the LQ decomposition when appending only one column to block Hankel matrix. To speed up the computation for on-line and almost real time computation, an advanced algorithm to update the LQ decomposition when appending more than one column to block Hankel matrix is proposed. Through this process there is no need to conduct the LQ decomposition on the new Hankel matrix for each recursive procedure which can reduce the computation time to extract the system dynamic characteristics. Detail about it can be found in reference [2].

It is important to note that to extract the system dynamic characteristics from the observation matrix, distinguish the true modes from the noise modes becomes a very critical issue. The system order n based on the singular value decomposition (SVD) of observation matrix $\mathbf{O}_i$ was first determined. Through the use of singular value decomposition (SVD) the system order *n* can be determined from the singular value greater than the assign value. Then output modal accuracy correlation (OMAC) and weighted phase error (WPE) procedures can sequentially be used, and the true modes can be distinguished from the noise modes [3]. Figure 4 shows the identified time-varying system natural frequencies of the bridge structure by considering all the measurements from the deck to form the data Hankel matrix for RSSI. It is observed that the change of system dominant frequencies in relating to the scouring depth and the pier settlements is closely related. It is important to point out that prior to the *t=7800 sec* (significant settlement at pier No.3) the change of system dominant frequencies can be observed.

4. DAMAGE DETECTION AND LOCALIZATION

Different from the detection of time-varying system natural frequencies, more significant features which can not only identify the damage but also detect the damage locations need to be explored. Through vibration-based monitoring data the on-line damage location was investigated.

4.1 Application of Cross-correlation Function Amplitude Vector

To avoid the limitation of the model-based damage detection techniques and considering the need of on-line damage detection, the concept of cross correlation analysis can be used. One simple approach is to test the cross-correlation from two measurements at the same time. Consider two random signals the correlation, $x_k(t)$ *and* $x_i(t)$, the correlation coefficient between these two signals is defined as:

$$\rho_{kj} = \frac{\int_0^T x_k(\tau) x_j(\tau)\, d\tau}{\sqrt{\int_0^T x_k^2(\tau)\, d\tau} \cdot \sqrt{\int_0^T x_j^2(\tau)\, d\tau}} \tag{1}$$

where "T" is the time window selected for estimating the correlation coefficient. It is believed that for an intact structural system the correlation coefficient ρ_{kj} between two measurement nodes, *k* and *j*, should be higher than the damage structure. Suppose more than two measurements are taken, the concept of cross correlation function amplitude vector (**CorV**) of the responses of a structure can be used [4]. It is defined the **CorV** as:

$$\mathbf{CorV} = \{ r_{k1} \quad r_{k2} \quad r_{k3} \cdots\cdots \quad r_{kn} \} \tag{2}$$

where r_{kl} is the maximum value of the cross correlation function between $x_k(t)$ *and* $x_l(t)$ $(l = 1, 2, 3, \dots, n)$:

$$r_{kl} = \max(\left| R_{kl}(\tau_l) \right|) = \lim_{T \to \infty} \frac{1}{T} \int_0^T x_k(t)\, x_l(t + \tau_l)\, dt \tag{3}$$

Since that the **CorV** is a vector, so it can be normalized as follows:

$$\overline{\mathbf{CorV}}(i) = \frac{\mathbf{CorV}(i)}{\left|\sum_j \mathbf{CorV}^2(j)\right|^{1/2}} \tag{4}$$

It is believed that the correlation coefficient between the measurement locations $x_k(t)$ *and* $x_i(t)$ in a structure should be close to one if the structure is not damage. Otherwise, the correlation coefficient will be low if damage occurred in the structure. In order to identify and quantify such a damage that occurred in the structure the correlation between two **CorV**'s is defined:

$$\mathbf{CVAC} = \frac{[\sum \mathbf{CorV}(j)\mathbf{CorV}^*(j)]^2}{\sum[\mathbf{CorV}(j)]^2 \sum[\mathbf{CorV}^*(j)]^2} \quad \& \quad \mathbf{CVAC} \in [0,1] \tag{5}$$

where **CorV** (j) and **CorV***(j) indicate the correlation coefficient of two different state, one is the reference state and other is the damaged state (or data calculated from different time period to express the different situation to the reference state). Higher CVAC value indicates higher correlation between the two states.

From the monitoring data of bridge scouring test, first, using Eq.(1), the correlation coefficient between two measurement locations is calculated. It is assumed that data from the sensor location No.1 is considered as the reference measurement. For a fix time window the correlation coefficient between the monitoring data from the reference location and the other measurement location can be generated. Correlation coefficient with moving time window of 20.0 sec, is generated and shown in Figure 5. It is observed that a significant drop of correlation coefficient with respect to the reference measurement location (sensor No.1) was observed at time *t=7800* sec. which is in consistent with the results from time-frequency analysis. the abnormal of correlation coefficient was also observed between *t=6000 sec* and *t=7800 sec*. Based on Eq.(5) CVAC was also calculated with respect to different reference data (measurement location). Figure 6 shows the calculated CVAC as a function of time by considering two different sensing nodes as references. A moving time window with time window of 20 sec was used. The first time window set of the data will be used as the undamaged set of data (or reference). From CVAC value one can detect the abnormal change of CVAC starting at *t=6000 sec,* which was identified as the prior information (or early warning message) to the significant change of CVAC which occurred at *t=7500 sec.* No matter which location was selected as the reference sensor node the CVAC value can still detect the damage. It is important to note that the CVAC can provide an early warning message before the significant change of the system dynamic characteristics (such as the dramatic drop of system dominant natural frequency).

4.2 Application of Proper Orthogonal Decomposition (POD)

Proper orthogonal decomposition is a procedure for extracting a basis for a modal decomposition from an ensemble of signals. If the response signal $q_k(t)$ of a discrete dynamic system with *m* degree of freedom (d.o.f.) are sampled *n* times and if the matrix ***Q*** is defined as

$$\mathbf{Q} = \begin{bmatrix} q_1(t_1) & \cdots & q_1(t_n) \\ \vdots & \cdots & \vdots \\ q_m(t_1) & \cdots & q_m(t_n) \end{bmatrix} \tag{6}$$

Then the proper orthogonal modes are the eigenvector of $\mathbf{G} = \left(1/n\right)\mathbf{Q}\,\mathbf{Q}^T$, and the corresponding eigenvalues are the proper orthogonal values. It had been proved that POMs are related to the vibration eigenmodes in some cases. Therefore, the POD should be an alternative way of modal analysis for extracting the mode shapes of a dynamic system. The POD was applied to the dynamic response data collected from the measurements of the bridge scouring test. Figure 7 shows the calculated time-varying first and second eigenmode. To evaluate the change of eigenmode along the time sequence, the initial calculated eigenmode was selected as the reference one; and then the root-mean-square error of the difference between the reference eigenmode and the eigenmode calculated from different time window is generated, as shown in Figure 8. It is observed that the abrupt change of time can be identified.

4.3 Damage Detection from Novelty Analysis

Different from the CVAC analysis, to conduct the structural damage diagnosis, based on the undamaged data the structural system matrix was estimated as a reference state. First, the reference data set was collected and the SSI algorithm was applied to estimate the undamaged state of the structural system. Based on the reference data set (the 1st initial data set is assumed as the reference data), the SSI method is applied to identify the undamaged system transition matrices $\mathbf{\Phi}_{k+1/k}$ which can be computed by exploiting the shift structure of the extended observability matrix.

The novelty analysis on system's dynamic responses is used to determine the bias of the predict responses if the system significantly deviates from initial baseline condition. The idea is to examine if the Kalman prediction model identified from the reference state data can be applied to newly measured data. Residual error can be estimated by comparing the predicted responses with the measured ones. The k-step state vector and the corresponding prediction error are calculated as:

$$\mathbf{e}_k = \mathbf{Y}_k - \hat{\mathbf{Y}}_k = \mathbf{Y}_k - \mathbf{M}_k \hat{\mathbf{X}}_k \qquad (7)$$

From the prediction error vectors $\mathbf{e}_k$ at any k-th sampling point, the Novelty index (NI) is defined as either Euclidean Norm or Mahalanobis Norm [5]:

Euclidean Norm: $$\mathbf{NI}_k{}^E = \| \mathbf{e}_k \| \qquad (8a)$$

Mahalanobis Norm: $$\mathbf{NI}_k{}^M = \sqrt{\mathbf{e}_k^T \Sigma^{-1} \mathbf{e}_k} \quad \text{with} \quad \Sigma = \mathbf{y}\,\mathbf{y}^T / N \qquad (8b)$$

The prediction procedure is performed using the data from the reference and actual states of the structure respectively. In the absence of damage, the level of prediction errors should remain unchanged. Otherwise, the Novelty index will change significantly for the damage case. Besides, the outlier statistical analysis, such as mean and standard deviation of **NI**, can also give a quantitative assessment of damage.

In Novelty analysis the identified system transition matrix needs to be estimated in advance, and the ordinary Kalman filter can be used to predict the state. The Kalman filter, in estimating the state consists of two estimates of the state $\mathbf{X}_{k+1}$: (1) a predicted estimate $\hat{\mathbf{X}}_{k+1/k}$ of the state $\mathbf{X}_{k+1}$ based on information up to the time $t = k\,\Delta t$ (consisting of observations $\mathbf{Y}_1, \cdots, \mathbf{Y}_k$); and (2) an update estimate $\hat{\mathbf{X}}_{k+1/k+1}$ which is obtained at time $t = (k+1)\,\Delta t$ when a new measurement $\mathbf{Y}_{k+1}$ is observed. For damage estimation the difference between the predicted estimate of state vector, $\hat{\mathbf{X}}_{k+1} = \mathbf{\Phi}_{k+1/k} \hat{\mathbf{X}}_k$ and the measurements is calculated. Recursive processing of the measurement data is applied through compute the predicted state and predict the observation $\mathbf{Y}_{k+1}$ and compute the update state. For damage assessment only the predicted measurements are used, the computed update state is only for the estimation of Kalman gain and the prediction error covariance.

To perform the Novelty analysis using the response measurement of bridge during scouring process, signals collected from all sensors (12 sensing nodes) are collected to form the Hankel matrix with dimension of $[1200 \times 7900]$. The time window is set to 40 sec. and with moving window of 40 sec. the first time segment will be used as the undamaged case. Figures 9 show the plot of the mean value of Euclidean Norm from each window was calculated from sensor node No.2 and No.9 respectively. It is observed that the mean value of Norm for each time window increase significantly at *t=6000 sec*. (particularly for data from sensor No.9 node) which was identified before the significant change of system dominant frequency. Comparison among the results from RSSI, Novelty analysis and the vertical deformation measurement at Pier No.3, one can detect the abnormal features from the vibration measurement before the significant settlement of bridge pier occurred. This Novelty analysis can also be used for early warning index.

4.4 Singular Spectrum Analysis for damage detection and early warning

The use of singular spectrum analysis is discussed as an alternative to traditional digital filtering method. Its usefulness has been proven in the analysis of climate and geophysical time series. SSA procedure consists of four steps: (1) embedding, (2) singular value decomposition (SVD), (3) grouping, and (4) reconstruction. The detail description of each step is shown in formal terms [6]:

With the concept of moving window (window length=40 sec) the data Hankel matrix was formed. This analysis can be done either for each sensing node or from all recorded sensing nodes. Through SVD the on the data Hankel matrix and eigenvalues were calculated. Figure 10(a) and 10(b) shows the difference between the first two largest eigenvalues from Node 2 and Node 9 measurement. This figure shows that prior to the significant settlement of the bridge pier No.3 at *7=7800 sec*, the distinct feature of the difference between two largest eigenvalues can be identified (at about *t=6000 sec*). This feature can be served as an index for early warning. This difference on the first two largest eigenvalues can also be calculate from all set of measurements instead of using data from a single sensing node, as shown in Figure 10(c) (plot in log scale). Through the reconstruction process of signal in SSA by using only the first two largest eigenvalues, comparison between the original signal and the reconstructed signal was made. The reconstruction is using the moving window technique by selecting the time window of 40 sec and with moving window of 40 sec. The size of the Hankel matrix is set to 600×7951. The root-mean-square (RMS) error between the reconstructed and recorded signal is plotted and shown in Figure 11. It is observed that the RMS error of the sensor signal from node 9 shows a significant change (around *t=5800* sec) before the large settlement occurred. This indication can also provide an early warning index.

5. FIELD EXPERIMENTS

Long-term ambient vibration data of Nu-Do Bridge at Yilan is collected in order to validate the proposed methodologies. Wireless communication system for data transmission is used in this experiment, as shown in Figure 12. On Sept. 19, 2010, Fanapi typhoon invading Yilan area and significant rainfall was observed in the northern part of Taiwan. Figure 13 shows the photo of the bridge in normal weather condition and in Fanapi typhoon period. The vibration response of the Nu-Do Bridge is also collected during the Fanapi typhoon strike. Application of RSSI to the measurements is conducted before, during and after the flood period by using sensor node D5H and D14H. Time-varying system natural frequencies were observed from the data at sensor node D14H which was close to the main river course, as shown in Figure 14. Figures 15 show the damage detection analysis by using Novelty Index and SSA. It is clearly observed that all these indices can detect the change of abnormal condition from the measurements.

6. CONCLUSIONS

Development of structural diagnostic approaches, in-service monitoring of structures with sensor networks may serve an important tool to identify the system modal parameters automatically and evaluate operational health of structures during normal operation condition. Damage detection algorithms depend on the accuracy of the modal parameters estimates and the success of on-line structural health monitoring and damage detection on feature extraction from response data. The main objective of this study on structural health monitoring (SHM) for bridge structure during scouring process is to identify the features from the in-situ operational condition and to detect the changes when damage occurred. Recursive Stochastic Subspace Identification can be applied for the identification of time-varying system frequencies. With suitable selection of model parameters one can conduct these analysis in almost real time analysis.

As for damage detection and early warning, distinct feature will be extracted from measurements before the severe damage occurred. Four methods are proposed in this study. Through the experimental study on bridge damage caused by scouring in the laboratory, the time-varying dynamic characteristics and the damage features of the bridge can be identified. It is possible to detect the abnormal situation (or features) from the response measurements before the significant damage occurred.

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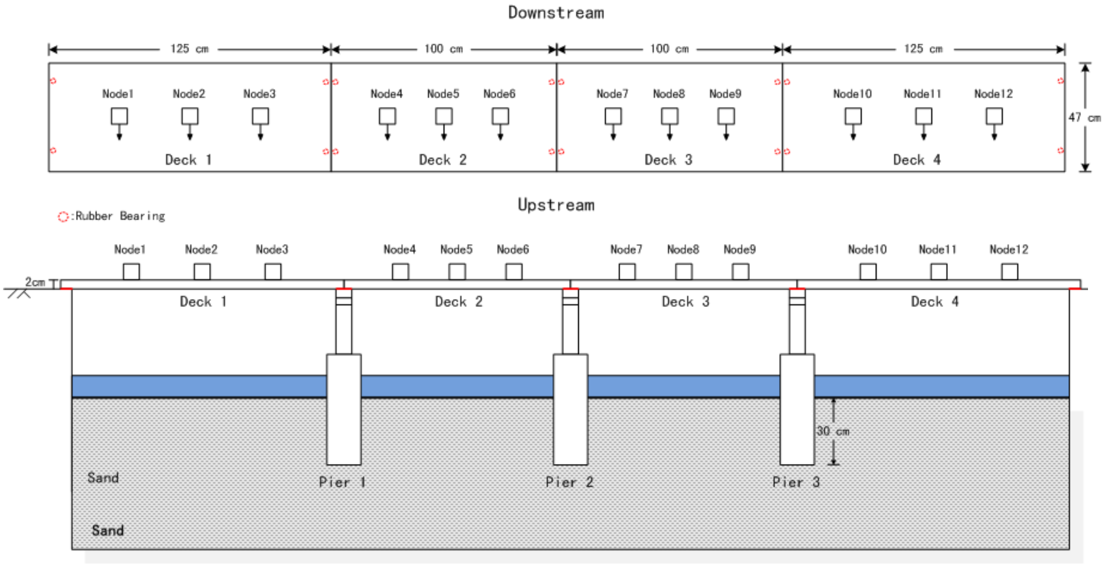


Fig.1: Sketch and dimension of the bridge test specimen

(a) during scouring test (b) after scouring test

Fig. 2: Photos of the bridge test specimen

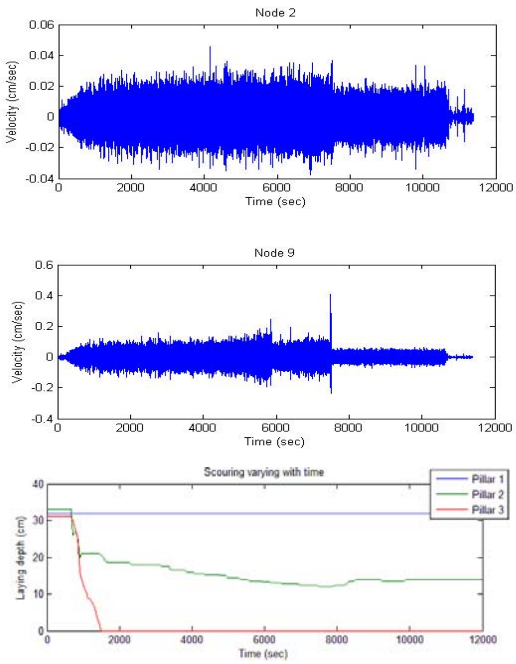


Fig. 3: Recorded velocity response from sensors at node 1 and node 9, and observation of scouring depth from each pier

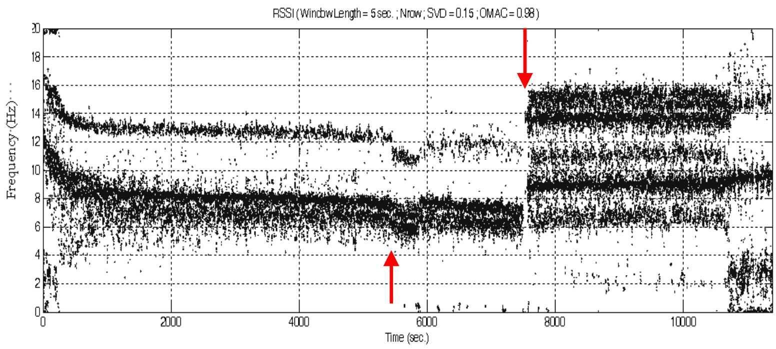


Fig. 4: Identified time-varying system natural frequencies using RSSI algorithm

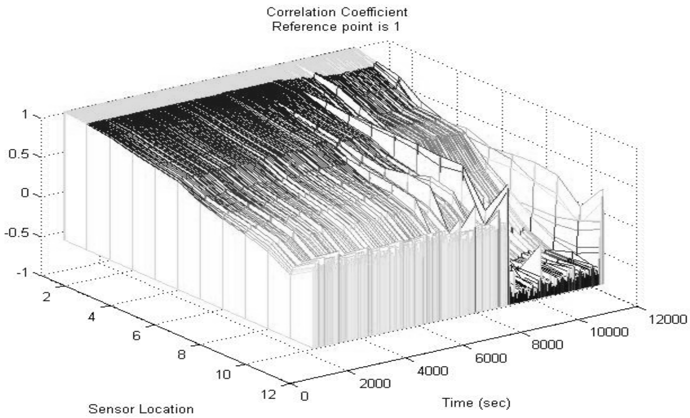
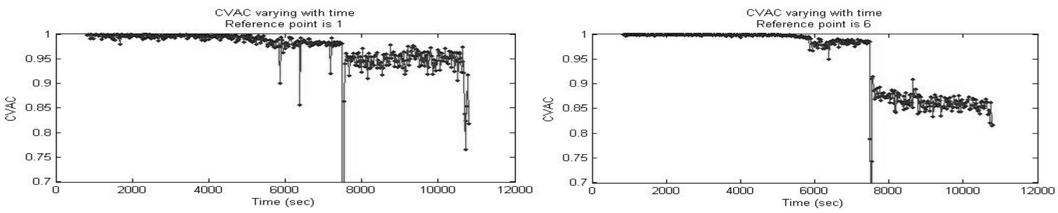


Fig. 5: Correlation coefficient with respect to sensor location and time



(a) (b)

Fig. 6: Plot of CVAC with respect to time; (a) consider sensor node No.1 as a reference, (b) consider sensor node No.6 as a reference

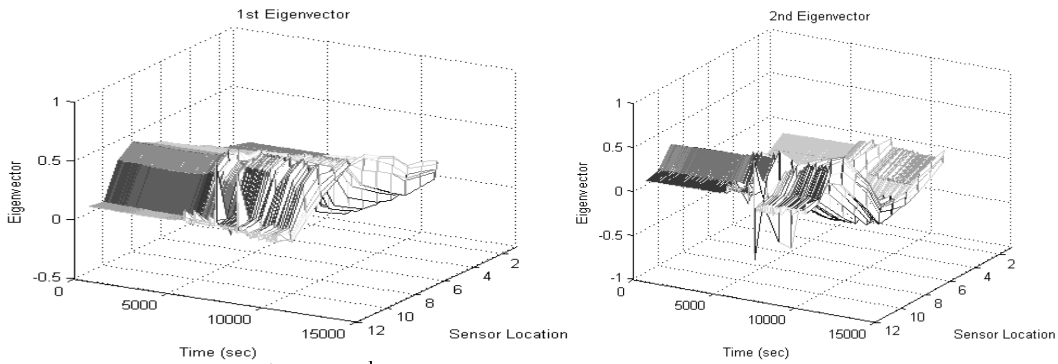


Fig. 7: Calculated 1^{st} and 2^{nd} eigenmode from Proper Orthogoanl Decomposition.

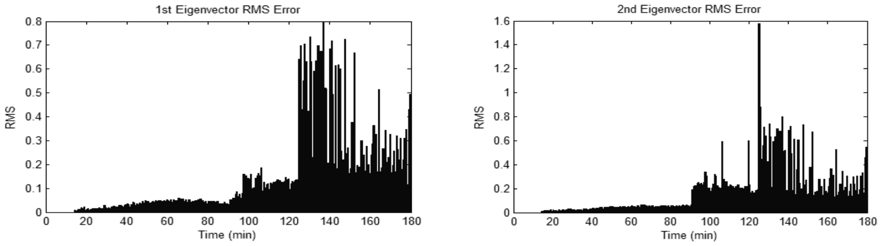
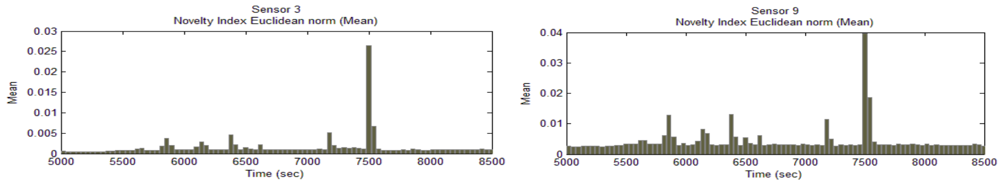
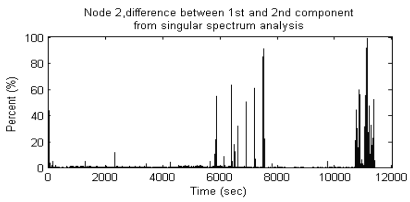


Fig. 8: Root-mean-square value of the difference between reference eigenmode and the eigenmode calculated from different time window.

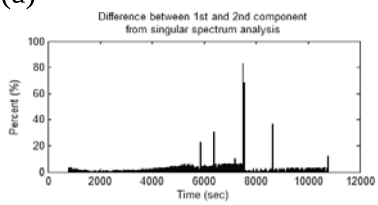


(a) (b)

Fig. 9: Mean value of time-varying Euclidean Norm; (a) response at Node 3, and (b) response at Node 9.



(a) (b)



(c)

Fig. 10: Difference between the 1st and 2nd eigenvalue-ratio from Singular Spectrum Analysis of the measured response at (a) Node 2; (b) Node 9; (c) All Node.

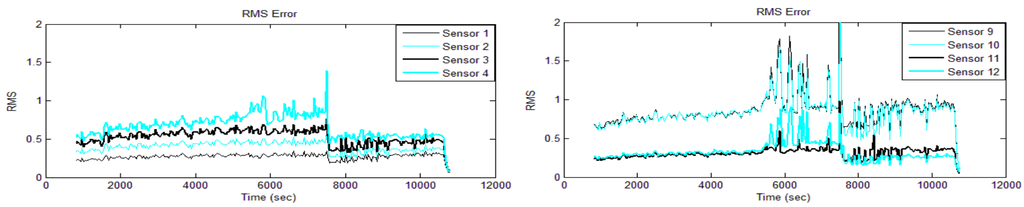


Fig. 11: Plot of RMS error between the measurement and the prediction using the reconstruction (from the two largest eigenvalues) wave forms of SSA.

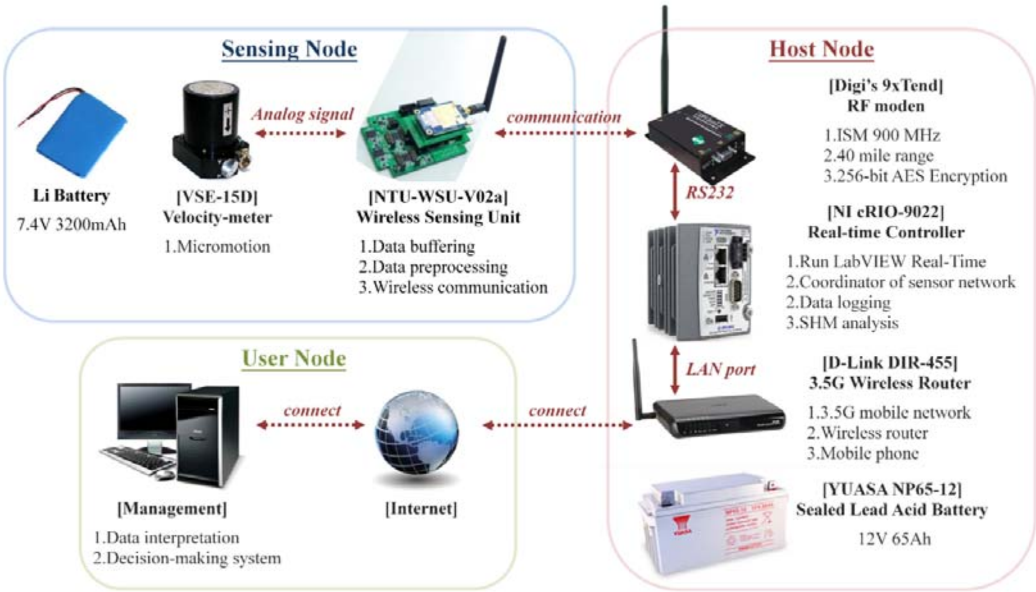


Fig. 12: Wireless data communication setup for field ambient vibration measurements.

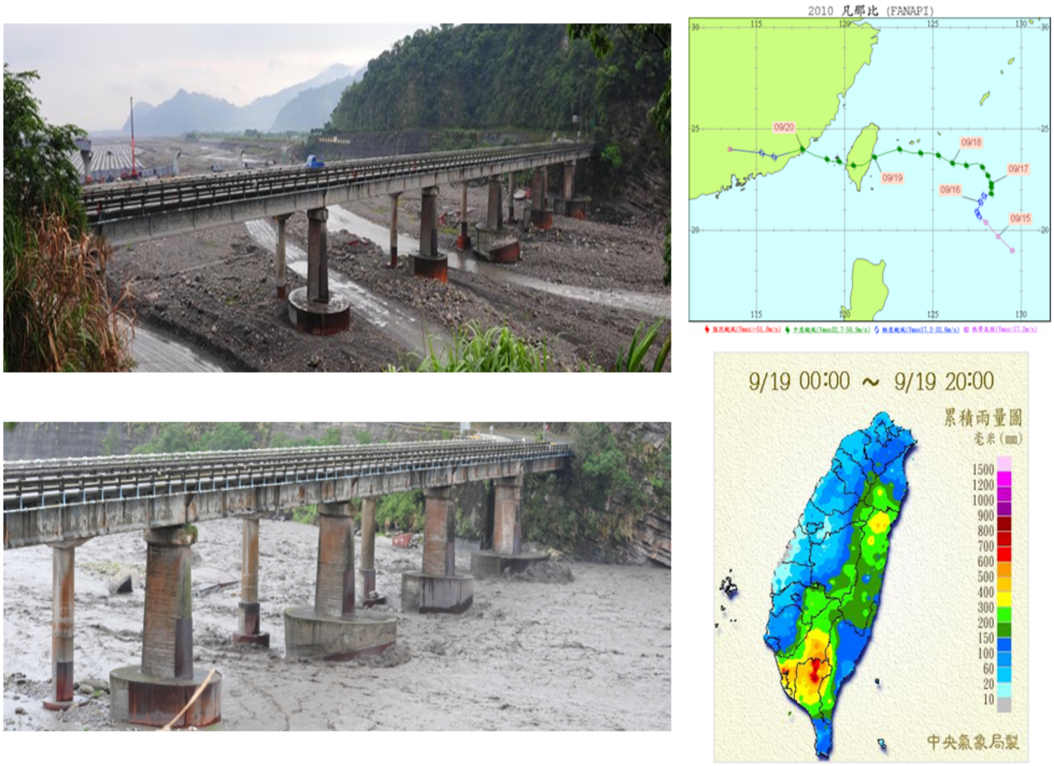


Fig. 13: Photos of the Nu-Dow old bridge before and during the typhoon period.

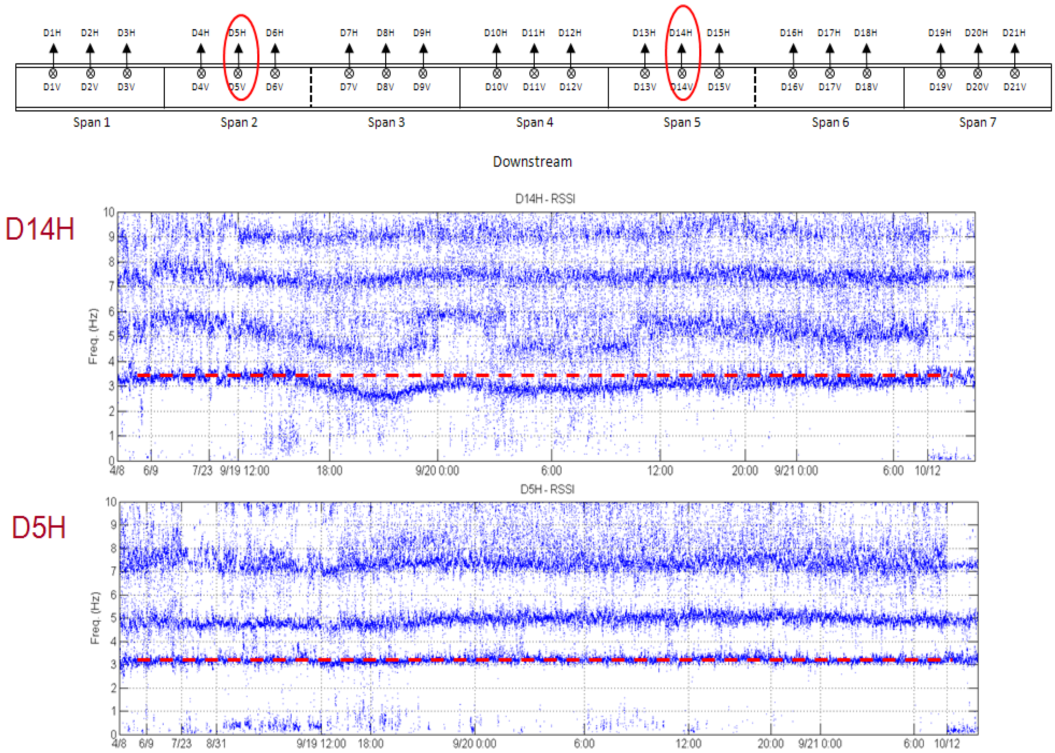


Fig. 14: Identified time-varying system natural frequencies from sensor nodes of D5H and D14H before, during and after the typhoon period.

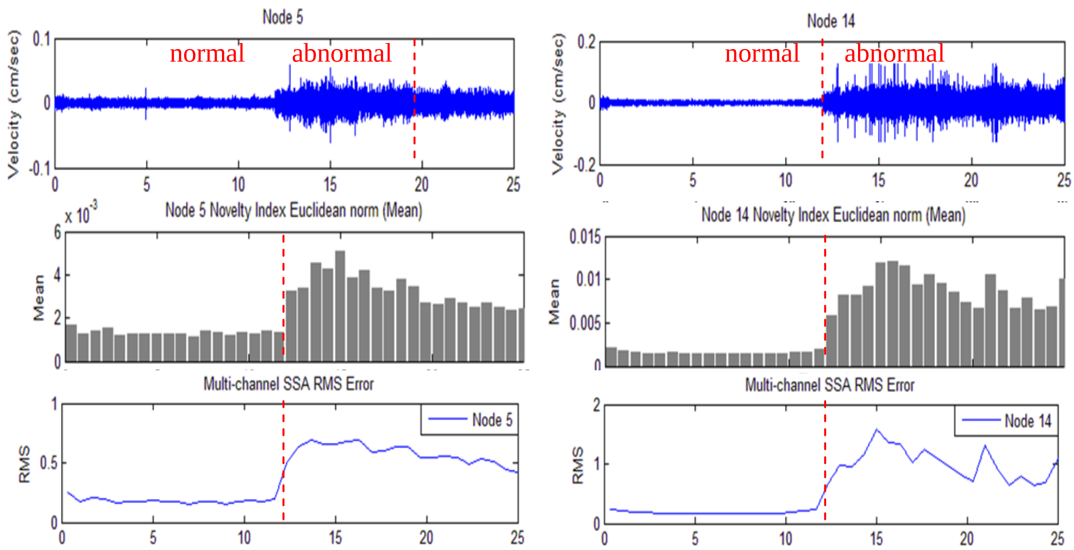


Fig. 15: Damage detection analysis by using D5H (Node 5) and D14H (Node 14) data of normal and abnormal condition during typhoon strike