Significance of Sensor Quality in Modal Identification of a Bridge Structure

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ABSTRACT

Advancements in sensing technology have improved the practice of structural health monitoring in different aspects. One of the distinguished developments introduced to the monitoring systems is deployment of wireless technology for data communication in a sensing network. While researchers have shown the effective role of wireless sensor networks in improving the affordability of structural monitoring systems, their possible impact on the reliability and accuracy of the results is still a research question. Some challenges in the design of wireless sensor units, such as the trade-off between the functionality and the power consumption, and also attempts for minimizing the cost, have caused limitations in their architecture which do not necessarily exist in the design of wired systems. On the other hand, depending on the subsequent application of the results of sensing and monitoring, the accuracy of measurements and the level of uncertainty in results can be very important. Therefore, it is necessary to carefully investigate the impact of sensor quality on monitoring results. As an effort towards understanding the effects of sensor quality on the results of structural monitoring, this paper presents and validates a metric, called Physical Contribution Ratio (PCR), which can be used to investigate the influence of measurement noise on modal parameter identification. This parameter in applied for quantification of measurement noise effects on the quality of modal identification of a steel bridge structure. Bridge's vibration is measured through use of wired and wireless sensors with different sensing qualities and the obtained results are compared through the use of the developed metric.

Keywords: structural health monitoring, wireless sensors, physical contribution ratio

1. INTRODUCTION

Modal identification of constructed structures is one of the fundamental steps in many structural health monitoring applications. Dynamic characteristics of structural systems enables assessment of the performance, calibration of finite element models, and assists with the maintenance of the structure over its life time. Vibration monitoring tests along with system identification approaches can provide modal parameters of the constructed structures. Over the past three decades, vibration monitoring techniques have improved from several points of view and the objectives of the improvements can be classified in different categories: enhancing the accuracy of results, minimizing the cost, and simplicity of the implementation.

Development and deployment wireless technology for data communication in a sensing network is one of the distinguished improvements, introduced to the vibration monitoring systems. This approach has shown its potential in improving the monitoring techniques in terms of cost and deployment [1- 5]. While the wireless sensor networks (WSNs) contributed in improving the affordability of vibration monitoring (ease of implementation and reducing the costs), their possible impact on the reliability and accuracy of the results still needs to be investigated. The main distinction between WSNs and wired systems (their traditional counterparts), is the wireless communication. However, some considerations in the design of wireless sensors, such as the trade-off between the functionality and the power consumption, and also attempts for minimizing the cost, cause limitations in the architecture of these sensor networks which do not necessarily exist in the design of wired systems. Despite the variety of available wireless sensing unit prototypes with different embedded sensors (e.g. accelerometers) presented in literature (mostly used in research

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Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2013,
edited by Jerome Peter Lynch, Chung-Bang Yun, Kon-Well Wang, Proc. of SPIE Vol. 8692,
869216 · © 2013 SPIE · CCC code: 0277-786X/13/$18 · doi: 10.1117/12.2009828

communities), the number of commercially available platforms with high quality sensors is limited. Thus, carefull investigation of the impact of sensor quality on modal identification is essential for broader application of wireless sensors.

An important factor in design of any sensing unit is the level of measurement noise. The embedded noise in the measurement data introduces an epistemic uncertainty into the results of system identification and depending on the following application of the results (e.g. damage detection) the level of this uncertainty can be very important and in certain situations misleading (e.g. in damage detection the uncertainty in the results may cause false alarms). Unfortunately, despite the development of a large variety of algorithms for system identification and implementations on structural systems [6-9], limited research have been conducted to investigate sources of uncertainty and their effects on the results. The limited research is mostly focused on the uncertainties associated with environmental and operational conditions such as ambient temperature, excitation characteristics, and data processing methodologies [10-15], and less attention is paid to the effects of measurement noise and the resulted uncertainties.

In practice of modal identification of in-service structures, investigation of the measurement noise effects is more challenging as monitoring environment usually imposes higher level of unwanted noise. In such environment, differentiating between noise effects and operational condition effects (e.g. random excitation), is difficult. A major challenge in investigation of measurement noise effects is that the existing accuracy indicators in modal identification are mostly relative indicators which are useful when comparing different identified parameters. Pappa *et al* [16 and 17] introduced Modal Amplitude Coherence and Modal Phase Collinearity that can be utilized to determine the confidence level of identified modal parameter when the ERA is used. These parameters are very helpful in selecting structural modes and differentiating them from the spurious modes. To indicate the general performance of the whole sensing system also, similar approaches and metrics are essential. Such metrics are also beneficial when comparing the performance of two sensing systems in terms of accuracy of results.

In this paper, the influence of measurement quality on modal parameter estimation, using ERA-NExT algorithm is evaluated. Physical Contribution Ratio is introduced, which reflects the level of contribution of physical modes in the estimation of impulse response versus noise and computational modes [18]. The developed metric is then implemented on data collected from the vibration monitoring of an in-service steel cantilever truss structure and the performance of the sensing networks are quantitatively evaluated. The sensing system of this vibration monitoring test includes wired and wireless networks with different sensor (accelerometer) qualities (i.e. accelerometers with low and high characteristic noise levels for measuring ambient vibrations). The performance of the two sensing systems in estimation of the Bridge's modal parameters is examined and the results are presented.

2. PHYSICAL CONTRIBUTION RATIO

In this section the physical contribution ratio (PCR) is introduced which represents the level of contribution of physical modes in the estimation of impulse response. In order to provide the background for derivation of PCR, basic formulations of the Natural Excitation Technique (NExT) and the Eigensystem Realization Algorithm (ERA) are also briefly presented.

2.1 System Identification Using ERA-NExT:

Natural Excitation Technique (NExT) is an approach which allows structures to be tested in under ambient loads [19]. NExT is based on the fact that the cross-correlation function between two measured displacements (or acceleration) of a structure satisfies the homogeneous differential equation of motion [20]. Consider the equation of motion for a multi-degree-of-freedom, linear time invariant system, and assume that the excitation is stationary random process, Equation of motion can be written as:

$$M\ddot{R}_{qq_i}(\tau) + C\dot{R}_{qq_i}(\tau) + KR_{qq_i}(\tau) = 0 \tag{1}$$

where M, C and K are N by N mass, damping and stiffness matrices, and $\ddot{q}(t)$, $\dot{q}(t)$ and $q(t)$ are acceleration, velocity and displacement responses at time t, and $R(.)$ denotes the correlation function (the correlation of the input of the system and the response, with positive lags will be zero as considered for the right hand side of the equation).

Equation 1 shows that correlation function of displacement satisfies the homogeneous differential equation of motion, and it can be also shown that the correlation function of acceleration response also satisfies the same equation of motion [21]. Therefore, for structural systems under ambient vibration (e.g. wind, traffic and ground motions), the impulse response can be estimated by computing the correlation function of their acceleration responses.

Having, [estimated] impulse response, many modal parameter identification algorithms can be applied to estimate the modal parameters. Among them, Eigensyestem Realization Algorithm (ERA) [6] is an effective and commonly used time-domain system identification techniques. This method uses the system's impulse response to derive system's parameters, without considering external force in its formulation. Considering the discrete-time state-space representation of the systems:

$$x(n+1) = Ax(n) + B\ u(n) \tag{2-a}$$

$$y(n) = Cx(n) + Du(n) \tag{2-b}$$

where $x(n)$ is the state vector at time step n, $y(n)$ is the observation vector at time step n, $u(n)$ is the input, and system's parameter A, B, C, and D are the discrete-time state, input, output, and matrices, respectively. In the ERA, to estimate the system's parameters the Hankel block data matrix is formed as:

$$H(n-1) = \begin{bmatrix} \hat{Y}(n) & \hat{Y}(n+1) & \cdots & \hat{Y}(n+q-1) \\ \hat{Y}(n+1) & \hat{Y}(n+2) & \cdots & \hat{Y}(n+q) \\ \vdots & \vdots & \ddots & \\ \hat{Y}(n+p-1) & \hat{Y}(n+p) & \cdots & \hat{Y}(n+p+q-2) \end{bmatrix} = \begin{bmatrix} CA^{n-1}B & CA^{n}B & \cdots & CA^{n+q-2}B \\ CA^{n}B & CA^{n+1}B & \cdots & CA^{n+q-1}B \\ \vdots & \vdots & \ddots & \vdots \\ CA^{n+p}B & CA^{n+p+1}B & \cdots & CA^{(n-3)+p+q}B \end{bmatrix} \tag{3}$$

where $\hat{Y}(n)$ is $N \times N$ (the number of outputs assumed to be equal to the number of inputs and equal to N) estimated impulse response matrix at the time step n ($\hat{y}_{ij}(n)$ is the estimated i^{th} output, due to an impulse at j^{th} input at time step n) and p and q correspond to the order of Hankel matrix. The right hand side of Equation 3 can be obtained by substituting the impulse function, as the input, into the Eq. (2-a) and (2-b):

$$\hat{Y}(n) = CA^{n-1}B \tag{4}$$

To extract the estimate of system's matrices, the Hankel data block matrix, $H(n\text{-}1)$, is decomposed using singular value decomposition (SVD) for $n=1$:

$$H(0) = P\Sigma Q^T \tag{5}$$

where P and Q^T are matrices of left and right singular vectors of $H(0)$ respectively, and $\sum$ is the diagonal matrix of singular values. Small singular values along the diagonal of $\sum$ correspond to computational or noise modes (nonphysical spurious modes). Thus, the rows and columns associated with nonphysical modes are eliminated from the singular-vector and singular-value matrices. The truncated matrices, $\sum_n$, P_n and Q_n are used to estimate the sate-space matrices for the discrete-time structural model as follow [6]:

$$\hat{A} = \Sigma_n^{-1/2} P_n^T H(1) Q_n \Sigma_n^{-1/2} \tag{6}$$

$$\hat{B} = \Sigma_n^{1/2} Q_n^T E_{inp} \tag{7}$$

$$\hat{C} = E_{out}^T P_n \Sigma_n^{1/2} \tag{8}$$

where E_{inp} and E_{out} are matrices of 1 and 0 with appropriate dimensions based on the size of inputs and outputs (*[I 0]*). Eigenvalue decomposition of the estimated state matrix results in the diagonal matrix of eigenvalues (Λ) and the matrix of eigenvectors (ψ) which give system's natural frequencies (ω_n 's), damping ratios (ζ_n 's) and mode shapes ($\vec{\phi}_n$'s).

2.2 Contribution Ratio of Physical Modes in Measured Signals

Physical Contribution Ratio (PCR) quantifies the participation of physical modal vibrations in the estimation of impulse response and modal parameters [18]. This metric is examined later, through implementation on data collected from ambient vibration test of Northampton Street Bridge.

Using NExT, the impulse response of the structure is estimated and can be used in the ERA for modal parameter estimation. PCR reflects the portion of this estimated impulse function which is driven from physical vibration as appose to noise related portion. The portion of estimated impulse function which is driven from structural modes (PCR) reflects the level of noise contamination in the modal identification process.

Consider the measured signal as a combination of structural response and the measurement noise, it can be written as:

$$y(t) = q(t) + n_s(t) \tag{9}$$

where $q(t)$ is the structural response and $n_s(t)$ is the stochastic noise in the measured data. The impulse response, $Y(\tau)$, is then estimated by the cross-correlation function of measured response as:

$$\hat{Y}(\tau) = R_y(\tau) = R_{qq}(\tau) + R_{nn}(\tau) + R_{qn}(\tau) + R_{nq}(\tau) \tag{10}$$

where R_y is a function of time delay or lag τ .

Based on the assumption that the measurement noise is uncorrelated with the response of the structure, the two last terms in the right hand side of Equation (10) will be canceled and the impulse response can be written as:

$$\hat{Y}(\tau) = R_{qq}(\tau) + R_{nn}(\tau) \tag{11}$$

Assuming that the noise characteristic is reflected in $R_n(\tau)$, Equation (11) shows that the measurement noise has a direct impact on the estimated impulse response. Also, it can be assumed that there is no correlation between measurement noises of different sensors and mainly the diagonal components of the correlation function are assumed to be contaminated by the measurement noise in the system.

As showed earlier, the *A*, *B* and *C* matrices of the discrete state space model can be estimated based on the estimated impulse response, using ERA. Equation 5 on the other hand relates the state matrices and the estimated impulse response. Transforming the system from physical coordinate into the modal coordinate ($A^n = \psi\Lambda^n\psi^{-1}$) changes Equation (5) to:

$$\hat{Y}(n) = C\psi\Lambda^{n-1}\psi^{-1}B \tag{12}$$

where ψ is the matrix of eigenvectors and Λ is the diagonal matrix of eigenvalues (λ_i's) in discrete form. Also, $C\psi = E_{out}^T P\Sigma_n^{1/2}\psi$ and $\psi^{-1}B = \psi^{-1}\Sigma_n^{1/2}Q_n^T E_{inp}$ are mode shapes and modal amplitudes, respectively, which are the outcomes of minimum realization in ERA. Mode shapes and modal amplitudes can be also written as:

$$C\psi = [\vec{\phi}_1 \quad \cdots \quad \vec{\phi}_m] \quad \text{and} \quad \psi^{-1}B = \begin{bmatrix} \vec{b}_1 \\ \vdots \\ \vec{b}_m \end{bmatrix}$$

where $\vec{\phi}_1$ to $\vec{\phi}_m$ are column vectors of mode shapes, and $\vec{b}_1$ to $\vec{b}_m$ are row vectors of corresponding modal amplitudes (the modal amplitude of a particular mode when impulse is applied at different nodes); *m* is the order of the system or the size of the state vector.

Expanding the estimated impulse response as sum of m identified modes of the system, Equation 15 can be written as:

$$\hat{Y}(n) = \begin{bmatrix} \vec{\phi}_1 & \cdots & \vec{\phi}_m \end{bmatrix} \Lambda^{n-1} \begin{bmatrix} \vec{b}_1 \\ \vdots \\ \vec{b}_m \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{m} \phi_{1i} b_{i1} \lambda_i^{n-1} & \sum_{i=1}^{m} \phi_{1i} b_{i2} \lambda_i^{n-1} & \cdots & \sum_{i=1}^{m} \phi_{1i} b_{iN} \lambda_i^{n-1} \\ \sum_{i=1}^{m} \phi_{2i} b_{i1} \lambda_i^{n-1} & \sum_{i=1}^{m} \phi_{2i} b_{i2} \lambda_i^{n-1} & & \\ \vdots & & \ddots & \vdots \\ \sum_{i=1}^{m} \phi_{Ni} b_{i1} \lambda_i^{n-1} & \cdots & \cdots & \sum_{i=1}^{m} \phi_{Ni} b_{iN} \lambda_i^{n-1} \end{bmatrix}_{N \times N} \tag{13}$$

where N is the number of outputs and b and ϕ are components of mode shape and modal amplitude vectors (e.g. ϕ_{ij} is i^{th} component of the j^{th} mode shape and similarly, b_{jk} is the j^{th} mode's amplitude at k^{th} location). This matrix of estimated impulse response presents each component of the estimated impulse response as the summation of contribution of all the estimated modes (in terms of mode shapes, modal amplitudes and eigenvalues).

Having the expansion for $\hat{Y}(n)$, the contribution of each mode can be extracted. As the impulse response is a function of time, the PCR parameter is defined by the integration over time (summation in discrete domain) which is a measure of signal's power. PCR of j^{th} mode in k^{th} diagonal component of estimated impulse response (auto-correlation function of signal with k^{th} node as the reference) is defined as:

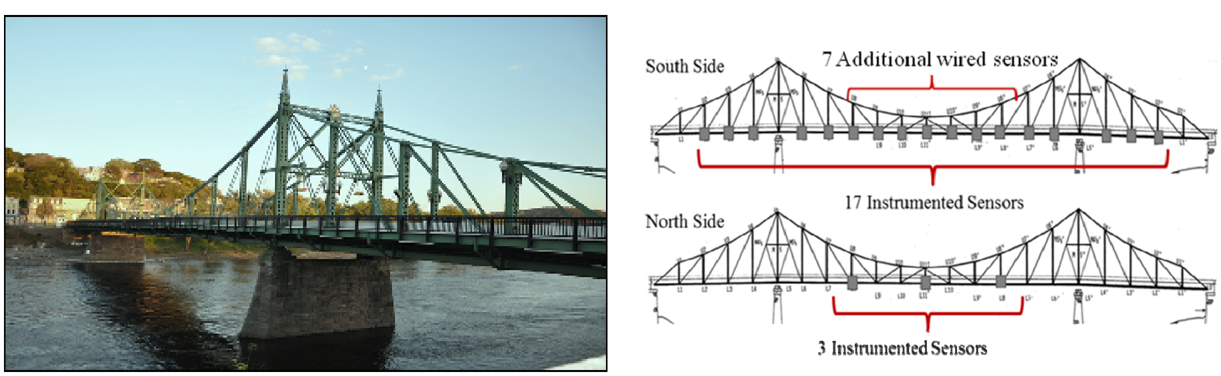
$$PCR_{kj} = \frac{\sum_n \phi_{kj} b_{jk} \lambda_j^{n-1}}{\sum_n \sum_{i=1}^{m} \phi_{ki} b_{ik} \lambda_i^{n-1}} \tag{14}$$

where n is the time index. When the noise contamination is constant for all the modes, it is evident that the higher PCR corresponds to less sensitivity of the mode to the noise (i.e. higher amplitude results in higher signal-to-noise ratio, in modal coordinate). Therefore, those modes with higher contribution in the auto-correlation function of a particular node are less sensitive to the noise level of corresponding sensor.

3. IMPLEMENTATION ON NORTHAMPTON BRIDGE

3.1 Vibration Monitoring of the Bridge

The structure of this study is historic Northampton Street Bridge located in Easton, Pennsylvania. A view of the bridge is shown in Figure 1(a). The structural system of the bridge is steel cantilevered-truss bridge with a total span of 550 (ft) supported by 2 piers. The span is divided into 25 (ft) sections such that each pier supports a 125ft cantilever on both sides and a 50 (ft) (two panels) section is suspended between them. The bridge has a three-ton weight limit, restricting traffic to small vehicles.



(a) (b)

Figure 1. (a) View of Northampton street bridge, located in Easton, PA, (b) instrumented sensing networks (wired and wireless sensors)

Vibration of the bridge under the ambient excitation, including the passing traffic, is measured using a wireless sensor network. The main objective of the monitoring is to investigate the effects of environmental and operational conditions (such as ambient temperature, random traffic loads, and also selected data processing algorithm) on the identified modal parameters. To this end, the vibration of the bridge was monitored throughout one year period, covering a variety of ambient temperature and traffic load levels. Thus, statistical study on the effects of these parameters on modal parameters could be performed. Further information regarding the obtained results can be found in [22]. Besides the effects of the mentioned parameters (ambient temperature, level of random traffic load and data processing algorithm), the effects of sensor quality and the uncertainty due to measurement noise is also to be investigated.

To evaluate the performance of the sensing systems and also for cross verification of results of wireless sensors, a network of wired sensors is also used during one of the field tests. The utilized WSN of this work includes 20 wireless sensor units with Imote2 [23] processing board (with Intel PXA271 processor and 32 MB SDRAM) and SHM-A [24] sensor board which integrates three-axial LIS3L02AS4 accelerometer [25] with ±2g acceleration range and 50 micro-g/√Hz noise level. The wired sensor network, on the other hand included low noise Silicon Design 2210-002 with ±2g acceleration range and 13 micro-g/√Hz noise level. Table 1 shows the different parameters of the accelerometers used in wireless and wired sensor units. The data acquisition system was PDAQ Premium system from DIGITEXX with 16 Channels for voltage input from different sensors types measuring with a 24 bit resolution analog filter. For cross-verification and comparison of measured data and results, only seven sensors of each network, located on the main span, were used. Figure 1(b) shows the instrumentation layout of the bridge with the two sensor networks.

The two sensing networks of this monitoring were tried to be approximately synchronized by having them start measurement at the same time. As the two sensing networks were controlled by two data acquisition systems, perfect time synchronization could not achieved. However, by having the two system start sensing at the same time, the same environmental and operational condition of the bridge can be assumed for the measured data of the two sensing networks.

Table 1. Specifications of the two accelerometers used in wireless and wired sensor networks.

Parameter	LIS3L02AS4	Silicon Design 2210-002
Acceleration range	±2 g	±2 g
Output noise	50 micro-g/√Hz	13 micro-g/√Hz
Sensitivity	0.66 v/g	2.00 v/g
Temperature Range	-40 to 85ºC	-55 to 125ºC

3.2 Data Processing and Modal Identification

Before performing modal identification, it is important to pass the data through a pre-processing (e.g. filtering and de-trending the data) serves to filter out high frequency noise to allow for the data to focus on the lower frequency content of the signals that correspond to the response of the structure. The data are collected from wireless sensors by 280 Hz sampling rate and are passed through on-board analog and digital filters. The on-board digital filter has cut-off frequency of 140 Hz. The collected data is further filtered with cut-off frequency of 70Hz through a cheby2 filter. The data from wired sensors are collected using 200 Hz sampling rate (5.00 milli sec. time interval) and are passed through the same filter as for wireless sensors. Figures 2 shows the power spectrum of an example acceleration data collected from the seven wired and the seven wireless sensors located along the main span. The collected data from the two sensor network are consistent and comparable. The different noise characteristics of the different utilized accelerometers in each sensing network make the frequency responses slightly different. This difference is basically negligible in identification of the modal properties. However, the identified modal properties may have different accuracy and purities.

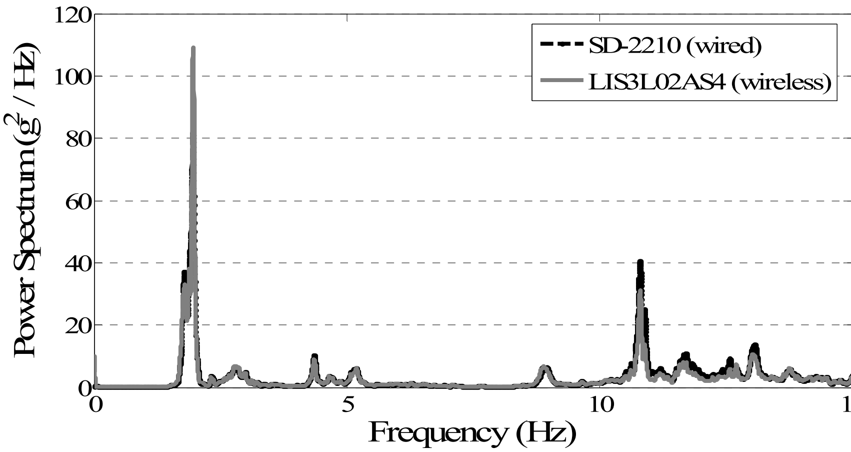


Figure 2. Power spectrum of the measured acceleration data from wired and wireless sensors.

As the main objective of the dynamic testing of a structure, modal properties are to be identified. Using ERA-NExT for modal identification of bridge monitoring allows data collection to take place anytime, when the bridge is under the random ambient and traffic loads. The data collected by two accelerometer sensor types from the ambient vibration of Northampton Bridge are used for modal parameter identification. Figure 7 shows the identified vertical mode shapes, resulted from the two sensor types.

A summary of identified natural frequencies and damping ratios of vertical modes, resulted from LIS3L02AS4 (wireless sensors) and Silicon Design 2210-002 accelerometer (wired sensors) data, are presented in Table 2. By comparing the modal properties, it is observed that both sensor types are capable of estimating the fundamental modal parameters of the bridge. However, some inconsistencies in results of two sensor types, particularly in higher frequency modes, and in damping ratios and mode shapes, are observed.

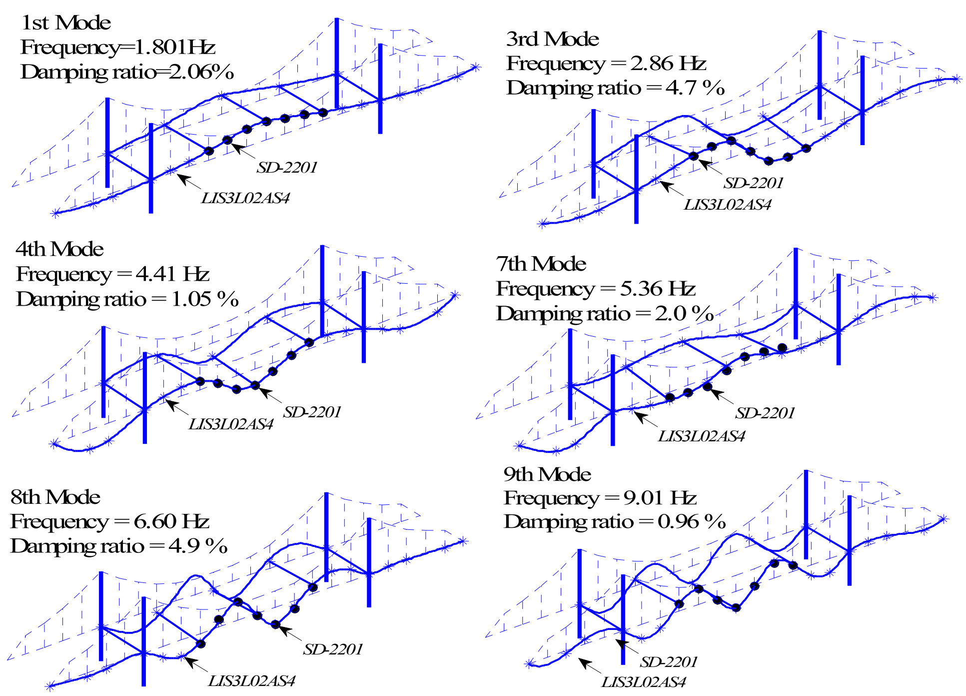


Figure 3. Estimated vertical modes of vibration of Northampton Bridge.

Table 2. Identified natural frequencies and damping ratios of vertical modes identified by ERA-NExT, using data collected by LIS3L02AS4 (embedded on SHM-A sensor board) and Silicon Design 2210 accelerometers.

Frequency (Hz)		Error (%)	Damping Ratio (%)		Error (%)	MAC (wd vs. ws)
SD 2210-002	LIS3L02AS4		SD 2210-002	LIS3L02AS4		
1.8099	1.8111	0.0618	0.0096	0.0108	11.0763	0.9991
2.7992	2.8122	0.4595	0.0334	0.0441	24.3110	0.9988
4.3940	4.3826	-0.2606	0.0400	0.0429	6.7477	0.9974
5.3205	5.3335	0.2435	0.0424	0.0451	5.9686	0.9491
6.4712	6.4344	-0.5713	0.0674	0.0702	4.0371	0.9941
8.9166	8.9366	0.2239	0.0177	0.0207	14.3675	0.9110

3.3 Application of Physical Contribution Ratio on the measured data

Comparison of the modal parameters identified through the use of the two sensor types indicates that there is an uncertainty coming from the measurement system. This highlights the need for a tool to quantitatively indicate the accuracy associated to each result. Note that all the parameters applied for process, such as filtering parameters in data pre-processing and model order in ERA system identification, are the same for both data sets when performing modal identification. This assures that the inconsistency in results is associated to their only difference which is the level of measurement noise.

Applying PCR on the estimated modal parameters, the performance of the two sensing systems, in terms of accuracy, can be investigated. The PCR of each mode is computed for different sensing nodes of the two sensing networks. Figure 4 shows these ratios for six vertical modes of vibration. It can be seen that PCRs are proportional to the modal ordinates. However, in addition to that, these ratios also depend on the modal amplitude factor (b) and modal frequency as can be observed in Equation 14. Since there are number modes (with natural frequencies in the considered frequency range in identification process) contributed in the measured response, contribution of each mode of vibration in the measured response is small. It is evident from the amplitudes of PCR values for different modes of vibration and different locations.

Figure 4 shows that the Silicon Design 2210, which has a lower noise level, presents significantly higher PCR, compared to that of LIS3L02AS4 which is embedded on SHM-A wireless sensor units. This means that the noise contamination of the estimated impulse response is higher in the LIS3L02AS4 sensors and thus, the estimated modal parameters are more influenced by the measurement noise. In theory, higher modes usually have less participation in response and therefore are more sensitive to the noise level. However, investigation of real data shows that some of the higher modes also have significant PCRs. This is understandable as the ambient excitation does not necessarily have a perfectly constant spectrum and thus, some higher modes may be excited more than others.

4. CONCLUSION

This paper presented the influence of measurement noise on the accuracy of modal parameter identification of a steel bridge structure. Physical Contribution Ratio (PCR) is introduced which examines the level of contribution of physical modes in the estimation of impulse response. PCR is implemented on the ambient vibration data of Northampton Bridge, which is measured by use of two different types of accelerometers in two sensing networks (LIS3L02AS4 and Silicon Design 2210) with different noise levels. To evaluate the effects of higher measurement noise, modal parameters identified by the two sensor types are compared and inspected in terms of accuracy using the presented parameter. The comparison of results, obtained from two sensor types, showed significantly higher PCR when using the low noise sensor data. The higher accuracy of results is essential for subsequent applications of the modal identification results and thus, such accuracy indicators are useful for evaluating the performance of sensing systems.While application of the presented metric (PCR) quantified the uncertainty of modal identification results associated with the measurement noise, further studies are essential to assess all sources of uncertainty (e.g. excitation randomness, ambient temperature, and effects of data processing parameters) exist in the modal testing environment.

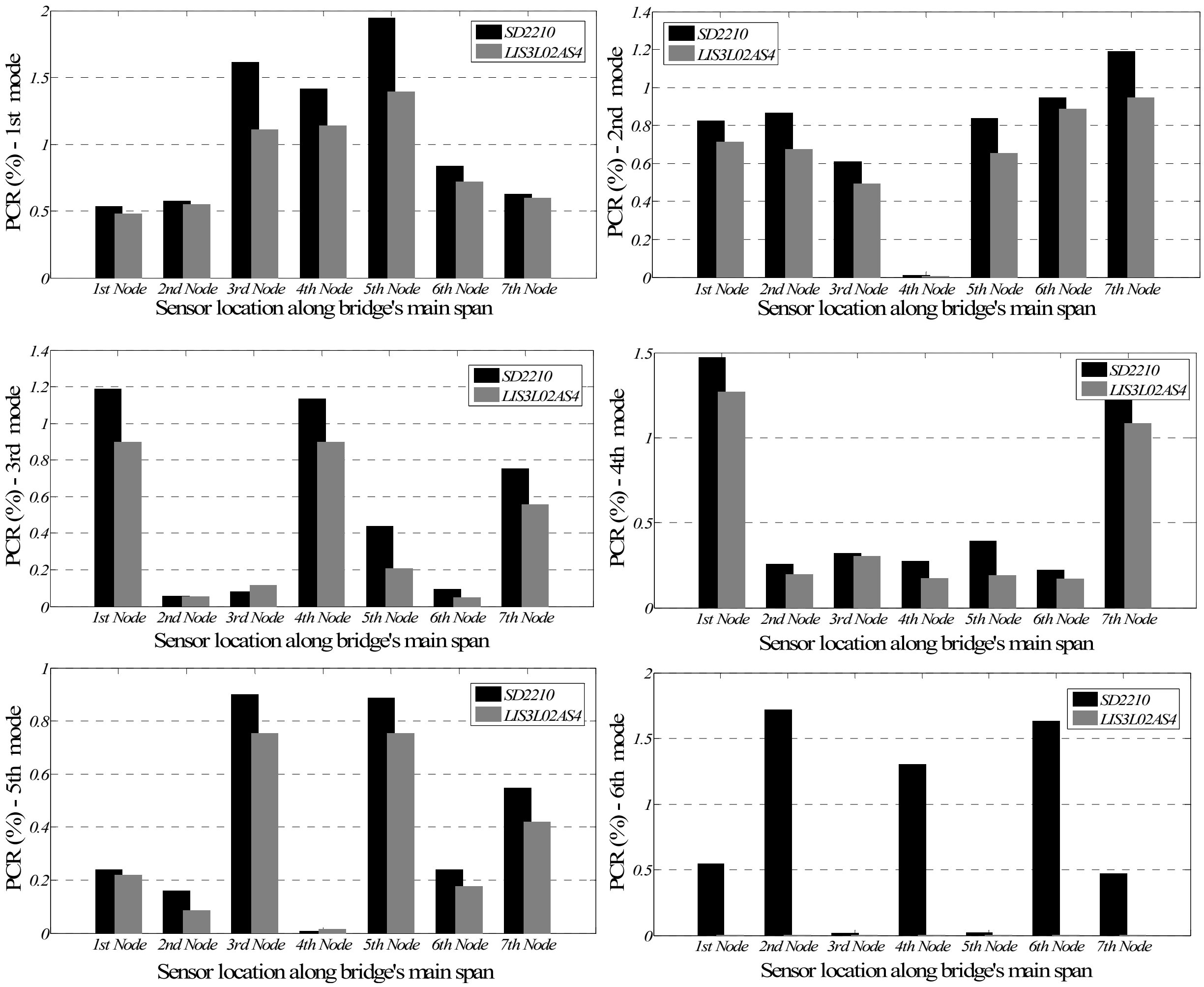


Figure 4. Physical Contribution Ratio at different locations for different modes.

ACKNOWLEDGEMENTS

The research described in this paper is supported by the National Science Foundation through Grant No. CMMI-0926898 by Sensors and Sensing Systems Program.

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