Mobile Sensors in Bridge Health Monitoring

T. J. MATARAZZO and S. N. PAKZAD

ABSTRACT

This paper will address a main concern in using mobile sensor data for SHM. Mobile sensors can offer comprehensive data similar to a “maximum fixed sensor networks” while keeping the simplicity of “minimum fixed sensor networks”. However, the data is expected to have an undesirable incompleteness feature and would not be readily compatible with modern SHM algorithms, e.g. feature extraction, data compression, system identification, traffic monitoring, reliability analysis, etc. requiring an additional model to compensate for incomplete data. This data-collection technique calls for a means to move sensors over a vibrating bridge, which could be implemented in a number of different ways. One example includes a vehicle (with onboard sensors) traveling over the roadway of the bridge to scan its vibrations in space and time.

INTRODUCTION

Identifying the current health of a structure is essential for assessing its response to future dynamic forces. As more information, spatial and temporal, is collected from a vibrating bridge, the structure’s can be evaluated more accurately. One may conclude that it is advantageous to implement as many fixed sensors on the structure as possible during data collection. Despite an improved accuracy in estimations, these maximum sensor or dense array approaches can be impractical for many reasons including sensor cost, setup cost, setup time, collection time, network reliability, power requirements, and physical limitations due to bridge geometries. While wireless sensor networks may reduce some of these challenges, the network is still comprised of fixed sensors. The ultimate flaw of fixed sensors is they provide limited spatial information.

MOTIVATION

Fixed sensors require a significant investment to produce a configuration that achieves a comprehensive density of spatial information. Mobile sensing offers the benefits of using a maximum fixed sensor network while significantly reducing setup

Department of Civil and Environmental Engineering, Lehigh University, ATLSS Engineering Research Center, 117 ATLSS Drive, Imbt Labs, Bethlehem, PA 18015, U.S.A.

efforts and the other challenges listed above. With this technique, only few sensors are used to collect data [1], however the data will include a large range of spatial information. The mobility of the sensors allows them to collect much less-limited spatial information. Mobile sensors are devices that are capable of recording the bridge response by "scanning" locations. The resulting dataset will contain the response recorded at varying locations over time. Additionally, by making data collection an overall easier process, users may feel more inclined to collect data more often, thus providing more up-to-date information on a bridge's health.

APPLICATIONS

Since mobile sensors do not refer to any specific devices, there are various data collection methods implementing them. The simplest form of mobile sensing can be illustrated by navigating a remote control toy-sized car, equipped with onboard sensors, e.g. Imote2 [2] or a smartphone, over the roadway of a bridge. Another form would simply substitute an actual vehicle in the previous setup; however, this specific case would have additional complications due to vehicle-bridge interaction.

Mobile phones have been used as mobile sensors in vehicles to broadcast real-time traffic data [3]. In this case, the data processing algorithms are regression based and include a learning component, combining data in the network as it becomes available. Additionally, some research shows the fabrication of specific mobile sensing units. Zhu et. al [4] created a mobile sensor node which collects data at a predetermined location and is capable of relocating on its own. Sibley et. al [5] and Dantu et. al [6] created Robomote, a small, inexpensive robot allowing mobile coverage of large-scale sensor networks.

In SHM, the applications of vehicles with mobile sensors have been limited. Partial system identification studies investigated determining modal parameters of a single bridge span using frequency domain techniques [7, 8]. Structural damage detection methods are also developing. Zhu et. al [4] used mobile sensor nodes and transmissibly function analysis and Cerda et. al [8] have shown preliminary results using short-time window Fourier transforms.

Vehicle-bridge interaction studies [9, 10] have established a framework describing how vehicle speed, path, and road surface conditions affect this interaction as well as the identification of a vehicle's modal properties using fixed sensor bridge data. Fortunately, this interaction can be controlled to some extent; more reliable results have been produced from vehicles traveling at lower speeds [7, 11]. Although higher vehicle speeds create larger bridge responses, the reliability of the results are "dubious" [12]. Lower speeds reduce complex behavior of the interaction by maintaining wheel-road contact, minimizing road surface effects, providing adequate frequency resolution in the response, and also are more appropriate for SDOF vehicle models. Similarly, vehicles with mobile sensors have been used for road surface monitoring [13], e.g. identifying potholes.

INCOMPLETE DATA

Figure 1 shows an example of a resulting fixed sensor data matrix using a dense fixed sensor array. This complete data matrix will have entries for all locations at all times. We can assume that data from a mobile sensor network is essentially sampled from the fixed sensor network data. So if the fixed sensors produce a complete data matrix, the mobile sensors would produce an incomplete data matrix. With knowledge of the path of the mobile sensors and assuming its sensing grid coincides with that of the fixed sensors, the mobile sensing data can be written directly in terms of the fixed sensor data.

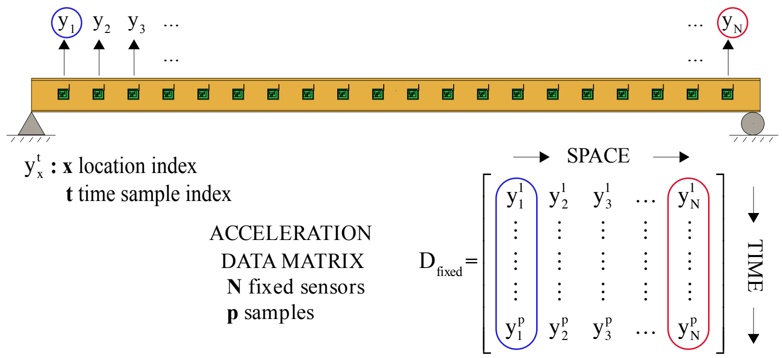

Figure 1. Example of resulting data matrix, D, from a dense sensor array

$$D_{fixed} = \begin{bmatrix} D^{t=1} \\ D^{t=2} \\ \vdots \\ D^{t=p} \end{bmatrix} \tag{1}$$

$$D_{mobile} = \begin{bmatrix} D^{t=1} \cdot M^{t=1} \\ D^{t=2} \cdot M^{t=2} \\ \vdots \\ D^{t=p} \cdot M^{t=p} \end{bmatrix} \tag{2}$$

Equation (1) shows how the collected data can be partitioned, representing each time step. In equation (2) the sampling matrix, M^t, is introduced. M^t is an N x N square matrix with binary indicators along its diagonal and zeros elsewhere; its purpose is to account for the data sampling mechanism and “mark” entries that have not been sampled. This is a direct result of the path of the mobile sensor(s). The sampling matrix must be defined at every time. Consequently, D_{mobile} is an incomplete data matrix.

A short example below shows a case where only one out of two sensors is used for the first sample and only the second sensor is used for the remaining three samples. The incomplete mobile sensor data matrix is derived from the complete fixed sensor matrix.

$$D_{fixed} = \begin{bmatrix} y_1^1 & y_2^1 \\ y_1^2 & y_2^2 \\ y_1^3 & y_2^3 \\ y_1^4 & y_2^4 \end{bmatrix} = \begin{bmatrix} Y^{(1)} \\ Y^{(2)} \\ Y^{(3)} \\ Y^{(4)} \end{bmatrix} \tag{3}$$

$$D_{mobile} = \begin{bmatrix} Y^{(1)} \cdot \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \\ Y^{(2)} \cdot \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \\ Y^{(3)} \cdot \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \\ Y^{(4)} \cdot \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \end{bmatrix} = \begin{bmatrix} y_1^1 & 0 \\ 0 & y_2^2 \\ 0 & y_2^3 \\ 0 & y_2^4 \end{bmatrix} \tag{4}$$

In the result of the example (4), the not sampled entries of the data matrix have been replaced with zeros. The mobile sensing data matrix can be written directly in terms of the fixed sensing matrix and the sampling matrices. This is just an example to illustrate the concept, so this substitution may not be appropriate for all cases. Also, depending on the incompleteness of D_{mobile}, its dimensions may be condensed for storage concerns. In mobile sensing, the incomplete data matrix will be sparse, i.e., there will be many more entries that are not sampled compared to the sampled ones. When considering data with such a large degree of incompleteness, interpolation attempts are futile; any attempt at this would essentially be a guess. Consequently, it is important to view this problem from a different perspective, in which we consider that each additional sample could increase or update bridge information.

Missing Data Problem

In this case, incomplete data can be considered as a form of the statistical missing data problem. The two most important features of this problem are the (1) parameter of interest (2) response mechanism. In other words, "what is to be estimated from this data set?" and "what pattern (or lack thereof) are data missing?". With these two questions addressed, an appropriate analysis strategy can be chosen. Little and Rubin [14] have categorized numerous missing-data with underlying statistical concepts. The missing data response mechanism is either known (KRM) or unknown (URM). This mechanism describes which values have been observed and which values are missing, for a data set $Y = [Y_{obs}, Y_{mis}]$ and can be represented as a categorical variable ("missing" or "not missing"). For the case of mobile sensing, the response mechanism will be known if the location of the mobile sensor is known at all times, i.e. in (4) M^t can be determined.

Although these strategies are commonly used in medical and social sciences [15], missing data strategies have been successfully applied to time series models [16]. Some applications include pollution data analysis [17], fishing dynamics [18], financial analysis [19], or traffic forecasting [3]. These studies use common time series models, e.g. state space, ARMA, which overlap with SHM models. Therefore, it is possible to develop a single model incorporating a missing data strategy within the SHM model, thus facilitating SHM when using data sets containing missing entries.

SYSTEM IDENTIFICATION EXAMPLE

In this section, an example will be presented that illustrates system identification using data sets with missing observations. System identification is a well-developed field in SHM in which the goal is to determine structural modal properties given its measured response. Such output only techniques, e.g. ERA-NeXT-AVG [20], are a practical choice when analyzing real bridge data [21, 22]. The following results use the noisy response of a simple undamped 10 DOF bridge system to white noise excitation. A hundred simulations were used to identify the first four modal properties of the structure. Next, at 10% of the time samples, the responses were removed from all locations at random, simulating a missing data problem. Although the missing data response mechanism was random, it is still known (KRM). The missing entries were replaced with the average values of the surrounding time steps. This replacement technique is known as imputation [23]. For system identification, a learning algorithm was used to update estimates from an output only ERA method.

Figure 2 and Figure 3 present the statistics of the identified frequencies over the number of simulations. In general, the identification was successful; but, there was a higher variance for the first mode. When 10% of the observations were removed at random, the results showed very similar behavior. In both cases, modes one through four were correctly identified and modes two through four had a low variance.

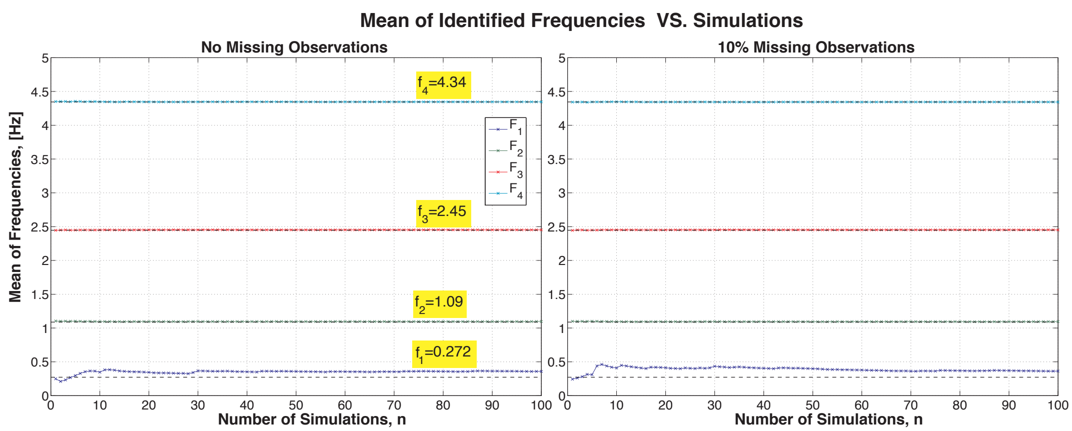

Figure 2. Mean estimated frequencies for complete and incomplete (10% missing) data

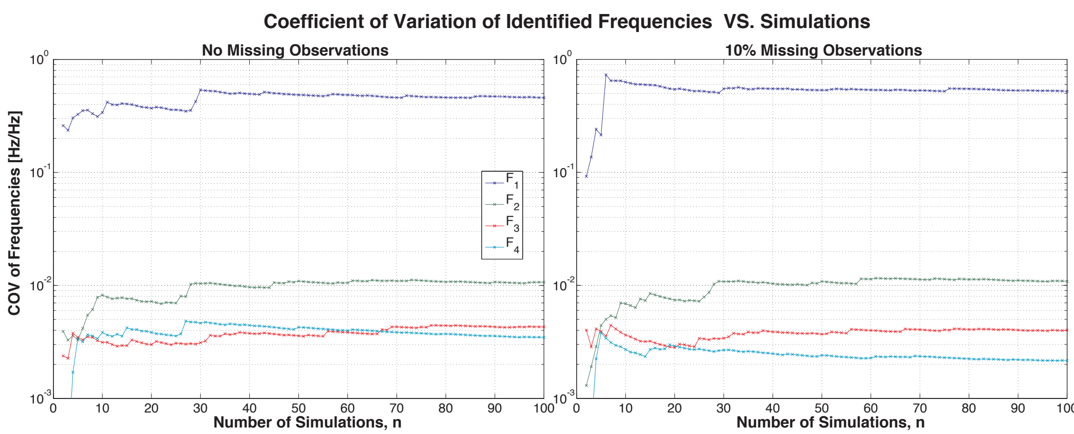

Figure 3. C.O.V. of estimated frequencies for complete and incomplete (10% missing) data

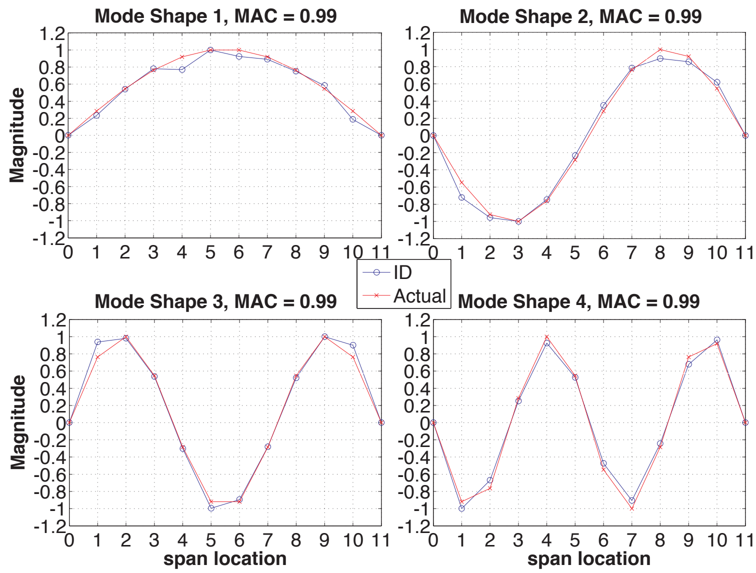

Figure 4. Mode shapes for complete data (from simulation 94)

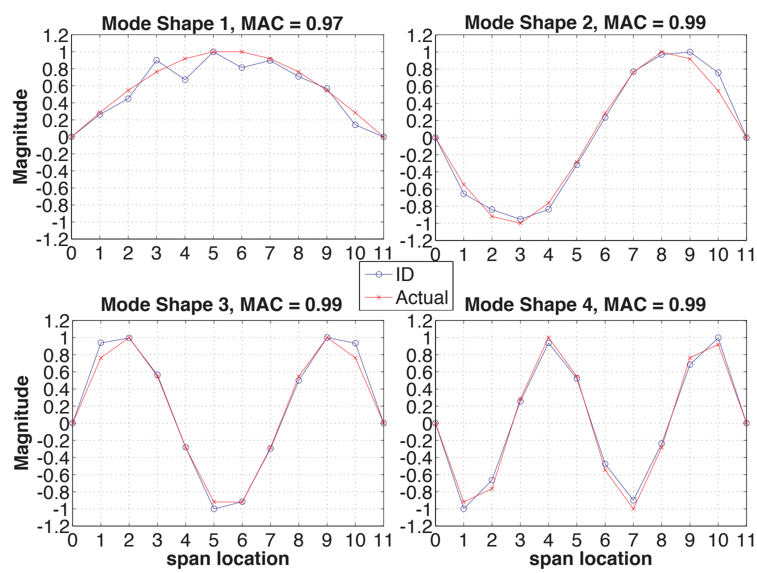

Figure 5. Mode shapes for incomplete data (10% missing, from simulation 94)

Figure 4 and Figure 5 present the first four mode shapes for a selected simulation (no. 94). For both complete and incomplete data, the mode shapes agreed with the actual solution. Visually, mode shapes two through four in Figure 4 and Figure 5 are the same with minor differences in MAC values (precision not presented). Figure 5 shows that the first mode shape became less accurate in the incomplete data case.

These preliminary results show that system identification is possible when the data contains missing observations. However, it is important to note that these results only reflect one specific missing data mechanism at a degree of missingness of only 10%. Also, the mechanism used in this example affected all sensing locations in the same manner. For mobile sensing applications, the incomplete data matrix will be sparse and the degree of missingness will be very high, e.g. 70-90% and the mechanism will be spatially active, affecting different locations at different times.

CONCLUSIONS

This paper provided a condensed overview of bridge health monitoring using mobile sensors. A literature review was presented to bring attention to recent research related to using mobile sensors in SHM. The current status of SHM in this field is still developing. New techniques are currently being studied and evaluated in experimental examples, however they haven't quite made their way to practice yet.

A short literature review on vehicle-bridge interaction has been presented identifying key parameters that ultimately effect what a mobile sensor would measure. It is important to note that after all, the interaction can be controlled to an extent, since we can control the speed and path of the vehicle. In short, lower vehicle speeds reduce complex interaction behavior, thus making simpler models, e.g. SDOF vehicles, more feasible for practice.

We have briefly discussed the origin of the incomplete data problem as a result of mobile sensors and linked it with the missing data problem in statistics. As long as we know the location and time of the samples, we can consider a known response mechanism in the model. Since SHM often uses statistical models in analysis, we have concluded that an efficient collaboration of models is possible, i.e., the structural system model will incorporate the complex observation model.

An example was presented to illustrate system identification using data sets with missing observations. The results show a rather successful identification of the first four modes of a 10 DOF bridge when missing data is present. However, while these results may be promising, they only reflect one specific missing data mechanism at a degree of missingness of only 10%. Mobile sensing will introduce much larger degrees of missingness with more complex missing data mechanism, which will drastically affect the system identification results.

REFERENCES

1. Unnikrishnan J, Vetterli M (2012) Sampling and Reconstructing Spatial Fields using Mobile Sensors. 2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). Ieee, pp 3789–3792
2. Nagayama T, Sim SH, Miyamori Y, Spencer BF (2007) Issues in Structural Health Monitoring Employing Smart Sensors.
3. Herring R, Hofleitnet A, Amin S, et al. (2009) Using Mobile Phones to Forecast Arterial Traffic Through Statistical Learning. 89th Annual Meeting of the Transportation Research Board. Transportation Research Board, p 21
4. Zhu D, Yi X, Wang Y, et al. (2010) A mobile sensing system for structural health monitoring: design and validation. Smart Materials and Structures 19:055011. doi: 10.1088/0964-1726/19/5/055011
5. Sibley GT, Rahimi MH, Sukhatme GS (2002) Robomote: a tiny mobile robot platform for large-scale ad-hoc sensor networks. Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat No02CH37292) 2:1143–1148. doi: 10.1109/ROBOT.2002.1014697
6. Dantu K, Rahimi M, Shah H, et al. (2004) Robomote : Enabling Mobility In Sensor Networks. 1:
7. Lin CW, Yang YB (2005) Use of a passing vehicle to scan the fundamental bridge frequencies: An experimental verification. Engineering Structures 27:1865–1878. doi: 10.1016/j.engstruct.2005.06.016
8. Cerda F, Garrett J, Bielak J, et al. (2012) Indirect structural health monitoring in bridges : Scale experiments. Proceedings of the Seventh International Conference on Bridge Maintenance, Safety and Management. Lago Di Como, pp 346–353
9. Cai CS, Chen SR (2004) Framework of vehicle–bridge–wind dynamic analysis. Journal of Wind Engineering and Industrial Aerodynamics 92:579–607. doi: 10.1016/j.jweia.2004.03.007

10. Yang Y-B, Lin CW, Yau JD (2004) Extracting bridge frequencies from the dynamic response of a passing vehicle. Journal of Sound and Vibration 272:471–493. doi: 10.1016/S0022-460X(03)00378-X
11. Mulcahy NL (1983) Bridge Response with Tractor-Trailer Vehicle Loading. Earthquake Engineering and Structural Dynamics 11:649–665.
12. Cantieni R (1992) Dynamic Behavior of Highway Bridges. 240.
13. Eriksson J, Girod L, Hull B, et al. (2008) The Pothole Patrol : Using a Mobile Sensor Network for Road Surface Monitoring.
14. Little RJA, Rubin DB (2002) Statistical Analysis with Missing Data, 2nd ed. 381.
15. Rubin DB (1996) Multiple Imputation After 18 + Years. Journal of the American Statistical Association 91:473–489.
16. Jones RH (1980) Maximum Likelihood Fitting of Time ARMA Models to Time Series with Missing Observations. Technometrics 22:389–395.
17. Robinson PM, Dunsmuir W (1981) Estimation of Time Series Models in the Estimation Presence of Missing Data. American Statistical Association 76:560–568.
18. Mendelssohn R, Roy C (1986) Environmental Influences on the French, Ivory Coast, Senegalese and Moroccan Tuna Catches in the Gulf of Guinea. ICCAT International Skipjack Year Programme. pp 170–188
19. Harvey AC, Pierse RG (1984) Estimating Missing Observations in Economic Time Series. Journal of American Statistical Association 79:125–131.
20. Chang M, Pakzad SN (2011) Modified Natural Excitation Technique for Stochastic Modal Identification. Journal of Structural Engineering. doi: 10.1061/(ASCE)ST.1943-541X.0000559
21. Dorvash S, Pakzad SN (2012) Effects of measurement noise on modal parameter identification. Smart Materials and Structures. doi: 10.1088/0964-1726/21/6/065008
22. Dorvash S, Pakzad SN (2012) Stochastic iterative modal identification algorithm and application in wireless sensor networks. Structural Control and Health Monitoring. doi: 10.1002/stc
23. Rubin DB (1987) Multiple Imputation for Nonresponse in Surveys. 258.