Chapter 33
Modal Identification of Golden Gate Bridge Using Pseudo Mobile Sensing Data with STRIDE

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Abstract This paper presents an application of a novel data collection method: mobile sensing. Mobile sensor networks can provide extensive information similar to dense fixed sensor networks while conserving the ease of smaller networks. However, mobile sensing data is expected to have missing observations in time and space, leaving data matrices incompatible with common identification techniques. STRIDE is an algorithm implemented for modal identification using this class of sensor data, which includes missing observations. Although mobile sensing devices are not widely available and large-scale mobile sensors networks have yet to be implemented, pseudo mobile sensing data is extracted from a dense sensor network using a simulated mobile sensor network. In this paper, ambient vibrations of Golden Gate Bridge are considered and pseudo (simulated) mobile sensing data are populated from a subset that shares the paths of simulated mobile sensors. The paper provides promising results to encourage the implementation of large-scale mobile sensor networks in future SHM endeavors.

Keywords Modal identification • Mobile sensors • Missing data • Signal processing • Structural health monitoring

33.1 Introduction

Proper identification and classification of the current health of a structure is essential to accurately assess its expected response to dynamic forces. As more spatial and temporal information is gained from a sensor network on a vibrating bridge, this accuracy improves. This may lead to the impression that more sensors (larger networks) necessarily provide more information and conclude that it is best to implement as many fixed sensors on the structure as possible during data collection. However, even though larger networks can contain an improved accuracy in modal property estimations [1, 2], it is important to choose carefully the sensor locations to maximize useful information, i.e. avoid collecting redundant data. Guo et al. [3] presented a genetic algorithm to provide optimal placement in structural health monitoring (SHM) and [4] introduced a methodology for system identification based on multiple models (chosen parameters).

Additionally, the efficiency of a dense sensor network array can be diminished by sensor cost, setup cost, setup time, collection time, network reliability, power requirements, and physical limitations due to bridge geometries [5, 6]. While wireless sensor networks may reduce some of these challenges, the network is still comprised of sensors that are fixed to one location. The ultimate flaw of fixed sensors is they provide limited spatial information.

Furthermore, it is advantageous to work with preliminary mobile sensing data before implementing a real mobile sensing network on a bridge to better assess its feasibility. In this paper, the preliminary mobile sensing data is referred to as pseudo mobile sensing data, which is, in short, a specific subset of a fixed sensor network's data matrix. The key is to choose sampling matrices that reflect a unique mobile sensor configuration. Once missing observations have been properly identified, appropriate alterations in a system identification algorithm can be considered.

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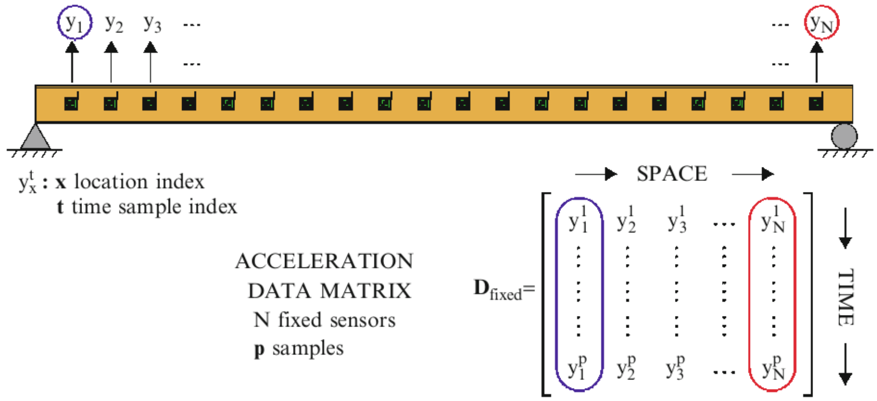

Fig. 33.1 Fixed sensor data matrix, D_{fixed}, from a dense sensor array [5]

33.2 Mobile Sensing Data

While recent applications within SHM have been diverse, they are limited, leaving the current state of mobile sensor networks as developing. Zhu et al. [7] created a moving sensor procedure which collected data at specific nodes, but did not record data while in-motion. Sibley et al. [8] and Dantu et al. [9] implemented Robomote, a small, inexpensive robot allowing mobile coverage of large-scale sensor networks. Partial system identification studies included a moving vehicle to investigate identifiability of frequencies for a single bridge span with frequency domain techniques [10, 11].

Mobile sensor networks offer the benefits of using a dense sensor networks while significantly reducing setup efforts and the other challenges listed previously. In these networks, fewer sensors can be used to collect data with less-limited spatial information [12, 13]. However, a side effect inherent in mobile sensing data is the anticipated missing observations in time and space—it is convenient to explain this issue by starting with a fixed sensor network.

Figure 33.1 shows an example of a fixed sensor data matrix resulting from a dense fixed sensor array. This complete data matrix will have entries for all locations at all times. Matarazzo and Pakzad [5] described how mobile sensing data can be written directly in terms of the fixed sensor data if the exact path of the mobile sensors is known and its sensing grid (spatial and temporal resolution) coincides with that of the fixed sensors'. This is expressed mathematically in Eq. (33.1), where M^t is an $N \times N$ sampling 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.

$$D_{mobile} = \begin{bmatrix} D_{fixed}^{t=1} \cdot M^{t=1} \\ D_{fixed}^{t=2} \cdot M^{t=2} \\ \vdots \\ D_{fixed}^{t=p} \cdot M^{t=p} \end{bmatrix} \tag{33.1}$$

Note the appearance of D_{mobile} depends entirely on the sampling matrices. For example, consider a single mobile sensor that hops to the next sensing location for every time step, resets to the first location d time steps after the last location, and repeats. Figure 33.2 shows the anticipated data matrix D_{mobile} for this given mobile sensor path. The observed values are exclusively located along specified diagonals. With this pattern in mind, the engineer can construct the appropriate sampling matrices and generate what appears to be mobile sensing data, from a readily-available fixed sensor data matrix: this is pseudo (simulated) mobile sensing data.

33.3 Pseudo (Simulated) Mobile Sensing Data

Again, pseudo (simulated) mobile sensing data can be extracted directly from a fixed sensor data matrix, i.e. without actually implementing a mobile sensor network, if and only if the paths of the mobile sensors are known or the sampling grid is consistent with the fixed sensors'. Given a fixed sensor data matrix D_{fixed}, the pseudo mobile sensing data matrix D_{mobile} is the subset of a fixed sensor network's data matrix that is specified in the sampling matrices.

This approach enables the engineer to analyze countless mobile sensor network setups without actually collecting additional data. These simulations can be used to assess the feasibility that a specified mobile sensor network is capable

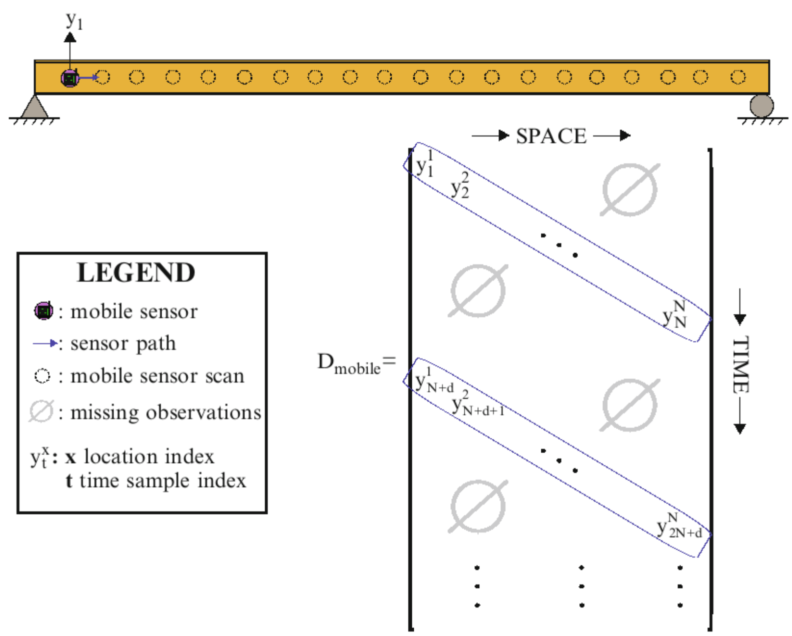

Fig. 33.2 Mobile sensor data matrix, D_{mobile}, for a specified sensor path

of successfully identifying the modal parameters of a bridge. While, in an actual mobile sensing network, there may be some additional complications not present in the pseudo data, e.g. space–time distortion [12] or vehicle–bridge interaction [14–16], it is essential to first establish the general applicability of a network.

Now that the collected data has been simulated with pseudo mobile sensing data, the resulting missing data problem as described in [5] is well constructed and an appropriate system identification algorithm may be selected under the condition that it can identify and process data sets with missing observations.

33.4 Structural Identification Using Expectation Maximization (STRIDE)

The Expectation Maximization (EM) algorithm [17–19] embedded in STRIDE provides an efficient method to identify structural modal properties using a stochastic state-space model (or AR model [20]). STRIDE iteratively converges to maximum likelihood estimates (MLE) of the model; the modal properties are calculated directly from these MLE. STRIDE is an attractive method in this case since the Kalman filter equations are modified at each "problematic" time step to account for missing observations [18, 21–24]. Note that in STRIDE, the actual imputed values for the missing observations in the mobile sensing data matrix are arbitrary.

33.5 Golden Gate Bridge Application

Golden Gate Bridge is an iconic steel suspension bridge that connects San Francisco, CA and Marin County, CA over the opening of the Pacific Ocean. The bridge has a total length of 8,981 ft (2,737 m), a center span of 4,200 ft (1,280 m), and carries six lanes of North/South car traffic and two sidewalks. The fixed sensing data consisted of 80,000 samples collected from 49 sensors at 50 Hz (a subset of the data in [1, 2])—this data was downsampled to 2.5 Hz. The network setup in Fig. 33.3 indicates 46 sensors on the West side of the bridge and three mirroring sensors placed on the East side of the bridge.

Simulated mobile sensing data was constructed on the basis of 46 mobile sensors traveling Northbound on the West side of the main span, with three stationary (fixed) sensors on the East side. Mobile sensors proceeded to the next sensing location, one by one, until the first sensor reached the North tower (after 46 time steps). Next, there was a delay of five samples (not applicable to three stationary sensors on the East side); after the delay, the pseudo mobile sensor train repeated, 51 time steps after the previous train began.

To reiterate, the total number of sensors on the bridge begins at four, increases by one each time step, until all 49 sensors are on the bridge. The total number of mobile sensors decreases to 41 during the five sample delay (stationary sensors

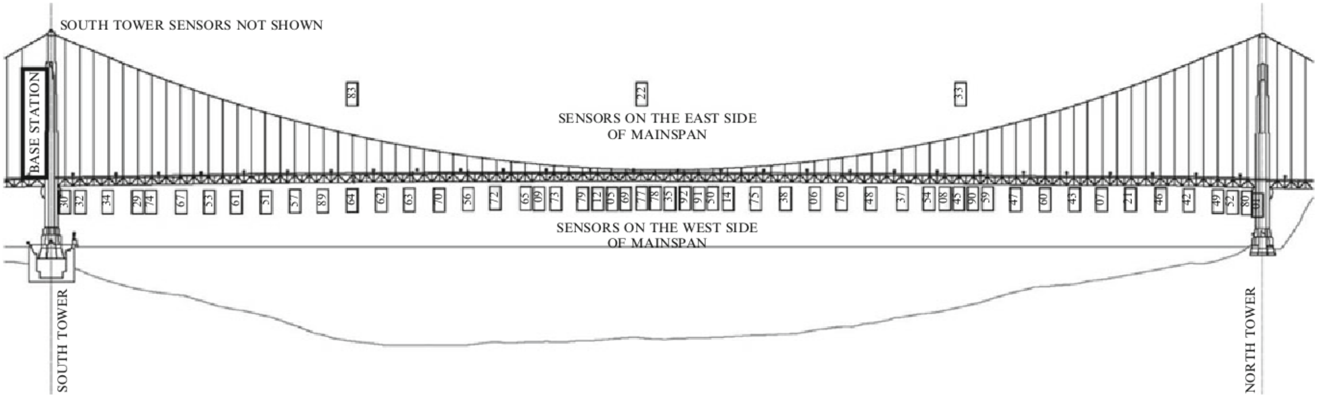

Fig. 33.3 Golden gate bridge sensor configuration [2]

Table 33.1 Estimated modal properties: "Fixed" denotes full data STRIDE, "M.S." denotes Mobile Sensors, and "Est." denotes results from [2]

Mode		1	2	3	4
Type		Anti-symm.	Symm.	Symm.	Anti-symm.
Frequencies (Hz)	Fixed	0.106	0.132	0.171	0.216
	M.S.	0.106	0.132	0.169	0.218
	Est.	0.106	0.132	0.169	0.216
Damping (%)	Fixed	2.14	1.80	4.82	1.56
	M.S.	0.14	0.43	0.13	0.48
	Est.	2.10	2.40	2.30	1.60

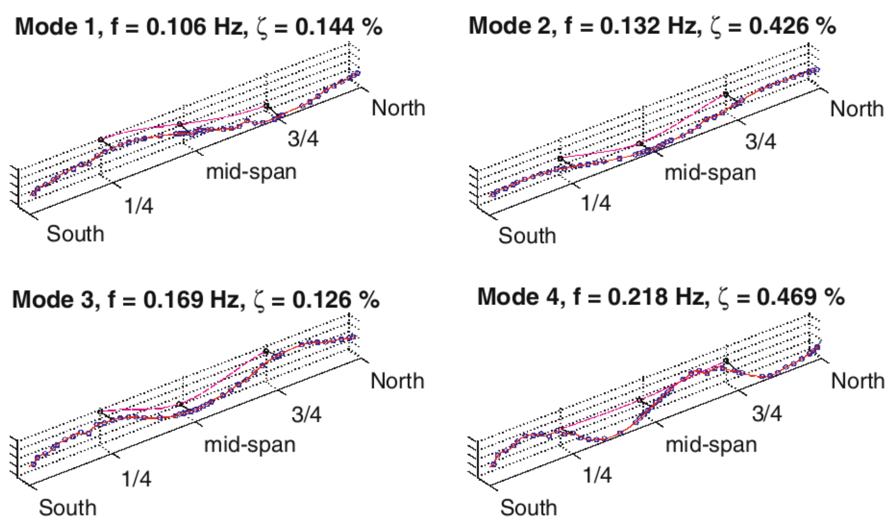

Fig. 33.4 First four identified modes from M.S. data

remain). Then, mobile sensors begin to re-enter from the South tower as sensors on the North end move off—this second phase repeats for the remaining data.

Table 33.1 provides a summary of the estimated modal properties. "Est." denotes modal estimates from [2] and "M.S." denotes those from the Pseudo Mobile Sensors with STRIDE. The first four vertical modes were identified successfully. Their frequency estimates were all within 1 % of those estimated in [2]. The damping ratios are also reasonably close considering that damping estimates are known to fluctuate based on the identification method and the model order [25].

In Fig. 33.4, the identified mode shapes are presented which are again consistent with the results in [2]. Note that in this simulation, D_{mobile} contained 10 % less observations than D_{fixed}. Additionally, the proposed mobile sensing network requires the setup o three fixed sensors as opposed to 49.

As mentioned earlier, a physical implementation of this mobile sensing network may face additional complications. For example, if the sensors travel over the bridge by vehicle, dynamic-vehicle bridge interaction is of concern. However, [16, 26, 27] have shown that lower speeds reduce complex behavior of the interaction by maintaining wheel–road contact, minimizing road surface effects, and provide adequate frequency resolution in the response.

33.6 Conclusions

This paper presented a preliminary modal identification study of Golden Gate Bridge using mobile sensors and STRIDE. Since data from mobile sensor networks are not widely available, pseudo (simulated) mobile sensing data are extracted from a dense network of fixed sensors. This pseudo mobile sensing data represents a unique set of mobile sensor paths that define the network configuration, i.e. locations of every sensor at each time step. The only condition for generating pseudo mobile sensing data in this manner is to ensure that the paths of the mobile sensors are known and the sampling grid (spatiotemporal resolution) is consistent with that of the fixed sensors'.

This technique enables the analysis of multiple mobile sensor network setups without requiring additional data collection. These preliminary simulations can be used to assess the feasibility that a specified mobile sensor network is capable of successfully identify the modal parameters of a bridge. This assessment is essential in justifying the implementation of large-scale mobile sensor networks.

A subset of ambient vibration data collected from Golden Gate Bridge was used to generate a pseudo mobile sensing network consisting of 46 moving sensors and three stationary ones. STRIDE was selected as the identification method because it is easily modified to process data with missing observations. The results included a successful identification of the first four frequencies, damping ratios, and mode shapes, indicating that the proposed mobile sensing network configuration is feasible for determining the first four modes.

Not only did the pseudo mobile sensing data consist of 10 % fewer observations, but the proposed setup included only three fixed sensors instead of 49 in the original data set. This application provides evidence to support real-world application of mobile sensor networks since setup efforts have been reduced and a successful modal analysis was performed using less data.

There are additional difficulties accompanying an applied mobile sensor network, which were not explicitly discussed in this paper, but at this time, from a data processing perspective, the concept is feasible. The analyses of additional mobile sensor networks may help determine optimal configurations for bridges on a case-by-case basis.

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